

DEPLOYMENT OF THE THIRD-GENERATION INFRARED CLOUD IMAGER:
A TWO-YEAR STUDY OF ARCTIC CLOUDS
AT BARROW, ALASKA

by

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TABLE OF CONTENTS

1. CLOUDS ON EARTH	1
Introduction.....	1
Methods of Collecting Cloud Cover Data	4
Earth Orbiting Satellites.....	5
Surface Observations by Human Observers	5
Lidars and Radars	5
Ground-Based Radiometers	6
Ground-Based Imagers	7
Motivation for a Ground-Based Infrared Cloud Imager	7
The Barrow Alaska Data Set.....	8
Organization of the Following Chapters.....	10
References Cited	11
2. INFRARED CLOUD IMAGING	16
Infrared Cloud Imaging	16
Advantages Over Visible Wavelength Imagers.....	17
Physics Principles of Longwave Infrared Cloud Imaging.....	18
The Atmosphere and Clouds in the LWIR	19
Need for Simulating the Atmosphere	23
Use of Microbolometer Cameras	25
The Montana State University Infrared Cloud Imager	26
ICI Generation 1	27
ICI Generation 2	28
ICI Generation 3	29
ICI Dome System.....	30
The Fourth-Generation ICI	31
A Legacy of Operation.....	32
Other LWIR Imaging Systems.....	33
The All Sky Infrared Visible Analyzer	34
The Whole-Sky Infrared Cloud-Measuring System	34
The Wide Angle LWIR Cloud Imager of Smith and Toumi	35
The Blue Sky Imaging All Sky Thermal Infrared Camera	37
Nubiscope	37
The Reuniwatt SIONS-T.....	38
The Radiometric All-Sky Infrared Camera.....	38
Cloud Height from LWIR Imagers	39
Cloud Optical Depth from LWIR Imagers	40
References Cited	41

TABLE OF CONTENTS - CONTINUED

3. THE THIRD-GENERATION INFRARED CLOUD IMAGER	47
Arctic Deployment Site	47
Instrument Design	49
Continuity with Previous Instruments	50
The Optics Enclosure	50
The Optical System	51
Hatch System	53
Internal Microcontroller	55
Instrument Communication	56
Computer and Control	56
Real-Time Operation and Software	57
Power Systems	59
Data Output	59
References Cited	61
4. INSTRUMENT CALIBRATION ARED CLOUD IMAGING	63
Introduction	63
Radiometric Calibration of the ICI Cameras	63
Temperature Sensitivity of TEC-Less Cameras	64
Observation with the ICI3 Camera	66
Microbolometer Temperature Model	67
Temperature of the Detector	68
Voltage Output	70
Simulation Results	71
Application of Calibration Algorithms	73
Removing FPA Temperature Dependence	73
Standard Radiometric Calibration of the ICI3 Data	75
Blackbody-Adjusted Radiometric Calibration	76
Deriving the Radiometric Calibration	78
Spectral Response Calibration	83
Derivation of the Spectral Response	84
Genetic Algorithms	85
Detector Noise	86
Noise Equivalent Temperature Difference	86
Noise Equivalent Radiance	88
Measurements of NER and NETD	88
Results of the ICI3 Noise Measurements	89
Geometric Camera Calibration and FOV Mapping	92
References Cited	99

TABLE OF CONTENTS - CONTINUED

5. DATA PROCESSING AND CLOUD DETECTION ALGORITHMS	102
ICI3 Data Processing	102
Atmospheric Propagation and Cloud Emission Models	103
Clear Sky Radiance Model	104
Sources of the Required Data	106
Uncertainty in the Clear Sky Radiance Model	107
Cloud Detection and Classification	107
The Cloud Detection and Optical Depth Thresholds	109
Uncertainty in the Cloud Detection Thresholds.....	110
Direct Cloud Optical Depth Relationship	111
Cloud Optical Depth with Cloud Height and Temperature	112
Considerations for Cloud Height and Atmospheric Emission.....	113
Cloud Detection Algorithms	114
The Direct Cloud Detection Method.....	114
Adaptive Data Processing	115
Correcting the Simulated Sky Radiance and Cloud Detection	115
Detecting the Clear Sky	117
Clear Sky Identification by a Support Vector Machine (SVM)	120
Support Vector Machines	121
Application to Cloud Remote Sensing.....	123
SVM Implementation in the ICI3	124
Kernel Selection.....	125
Building the Training Dataset.....	125
SVM Development	126
Final Features Selected for the SVM.....	127
Cloud Classification with a SVM	130
Validating the Cloud Classification Algorithms.....	131
References Cited	132
6. INSTRUMENT ACCURACY	135
Cloud Detection Accuracy	135
Uncertainty in the Cloud Data Processing.....	135
Uncertainty in the Measured Signals	136
Uncertainty in the Atmosphere Model.....	137
Uncertainty in the Residual Radiance.....	137
Hypothesis Testing Approach to Cloud Detection	138
Uncertainty in the Atmosphere Model.....	142
Atmosphere Model Parameters.....	143
Uncertainty Due to the Field of View.....	145
ICI3 Atmosphere Model Accuracy	147

TABLE OF CONTENTS - CONTINUED

Uncertainty in the Radiometric Calibration.....	148
Additional Sources of Uncertainty.....	148
Dynamic Changes in the Calibration Uncertainties.....	148
Calibration Uncertainties Due to Extrapolation.....	150
Bandwidth-Dependent Uncertainty	151
FFC-Dependent Uncertainty	152
ICI3 Calibrated Measurement Accuracy	155
Application of the ICI Uncertainty Models	155
Noise-Equivalent Cloud Optical Depth	158
Minimum Detectable Cloud.....	159
Algorithm 1 Direct Cloud Detection.....	160
Adaptive Cloud Detection Algorithms	163
References Cited	166
 7. RESULTS OF THE BARROW DEPLOYMENT.....	 167
Deployment of the ICI at ARM NSA	167
Blackbody Calibration Analysis	168
Comparisons with the AERI.....	171
AERI Integrated Radiance	172
Uncertainty in the Spectral Response Function.....	172
Uncertainty in the ICI Zenith Radiance	173
Results of the AERI Comparison.....	174
Cloud Data Measured with the ICI3	184
Estimates of Uncertainty in the ICI3 Data	184
Comparisons Between Processing Routines	186
ICI-to-ARM Instrument Comparisons.....	188
Total Sky Imager.....	190
Multifilter Rotating Shadowband Radiometer.....	190
Sky Radiometers for Downwelling Radiation	191
Ceilometer Cloud LIDAR.....	191
Micropulse LIDAR	192
Baseline Comparisons.....	192
TSI Versus CEIL.....	193
MFRSR Versus CEIL	194
SkyRad Versus CEIL	195
MPL Versus CEIL	196
MFRSR Versus TSI	197
SkyRad Versus TSI.....	198
SkyRad Versus MFRSR	199
Summary of ARM Instrument Comparisons	200
Comparisons of ICI and the ARM Instruments	201

TABLE OF CONTENTS - CONTINUED

Comparisons of All ICI Processing Routines	201
ICI3 Versus TSI	203
SkyRad Versus ICI	204
MFRSR Versus ICI.....	205
CEIL Versus ICI	206
Analysis of the ICI SVM Processor.....	207
Cloud Occurrence Diagrams (Smile Diagrams)	209
Extended Sensitivity of the ICI3.....	212
Comparison with ARM Instruments.....	212
References Cited	217
8. CONCLUSIONS.....	219
Goal of this Project	219
Contributions of this Project	220
Understanding of Instrument Operation	220
Instrument Accuracy Analysis.....	220
Radiometric Comparisons with the AERI	221
Comparisons with Co-Located Cloud Instruments.....	222
Improved Data Processing	223
Gradient-and-Time (v4) Algorithm	224
The Cloud Classification Support Vector Machine	224
In Conclusion	226
REFERENCES CITED.....	228

LIST OF TABLES

Table	Page
2-1. Summary of the ICI deployments	33
3-1. Total system power draw	59
3-2. Enclosure power draw	59
3-3. Instrument Rack Power Draw	59
3-4. Variables saved in each data file	60
3-5. Data saved in the daily summary files	60
4-1. Summary of the calibration accuracy	82
4-2. Measurement of NER and NETD in the ICI3	92
4-3. Camera model parameters and uncertainties	97
4-4. Camera distortion model coefficients	98
4-5. Re-projection error	98
5-1. Optical Depth and Attenuation for the ICI2	110
5-2. Calculated Thresholds for the ICI3 at NSA throughout the year in W/(m ² sr)	110
5-3. Cloud Detection Uncertainty	111
5-4. Features derived from the sky imagery used in the SVM classification	128
6-1. Results of hypothetical cloud and clear sky detection.	140
6-2. Uncertainty in the atmosphere model parameters	142
6-3. Summary of the calibration accuracy	148
6-4. Uncertainty sources in the ICI3 modeling	156
6-5. Noise-equivalent cirrus cloud OD for 15 frame and single-frame acquisition	158

LIST OF TABLES - CONTINUED

Table	Page
6-6. ICI3 minimum uncertainty equivalent cirrus cloud	160
6-7. ICI3 camera and scene assumptions	160
6-8. System uncertainty.....	161
6-9. Cloud detectability for the direct cloud detection algorithm	162
6-10. Calculated threshold levels for the ICI3 compared to the system uncertainty.....	162
6-11. System uncertainty for the adaptive cloud detection algorithms	163
6-12. Cloud detectability for the adaptive cloud detection algorithms	164
6-13. Calculated threshold compared to the uncertainty of the adaptive algorithms.	165
7-1. Differences in the radiometric calibration sets	170
7-2. AERI - ICI3 differences using the 2016 standard calibration.....	182
7-3. AERI - ICI3 differences using the 2016 blackbody adjusted calibration	182
7-4. AERI - ICI3 differences using the 2012 standard calibration.....	182
7-5. AERI - ICI3 differences using the 2012 blackbody adjusted calibration	182
7-6. AERI - ICI3 differences using the band 51 blackbody adjusted calibration	182
7-7. AERI - ICI3 differences using a selective combination of the 2016 standard and blackbody adjusted calibrations.....	184
7-8. Calibration processing estimates.....	186
7-9. TSI versus CEIL	194
7-10. MFRSR versus CEIL	195
7-11. SkyRad versus CEIL.....	196

LIST OF TABLES - CONTIUED

Table	Page
7-12. MFRSR versus TSI.....	197
7-13. SkyRad versus TSI.....	198
7-14. MFRSR versus SkyRad	199
7-15. Inter-comparisons of the co-located ARM cloud instruments.....	200
7-16. Comparisons of the ICI with co-located ARM cloud instruments	202
7-17. ICI versus TSI.....	204
7-18. SkyRad versus ICI	205
7-19. MFRSR versus ICI.....	206
7-20. ICI versus CEIL	207

LIST OF FIGURES

Figure	Page
2-1. Example data taken with a 110° field-of-view ICI showing clear sky (dark blue), thin clouds (light blues) and thick clouds (yellow and red): (a) radiance; (b) cloud optical depth.....	19
2-2. Simulated transmittance for the US76 atmosphere (ground level 2.29 km above sea level) with water vapor profiles using default (black) and 1.5x default (red) values.	20
2-3. Down-welling atmospheric emission spectra for US76 atmosphere with 1.5x default water vapor (red, top), and US76 atmosphere (black, bottom).....	21
2-4. Down-welling emission from a cloudy and clear atmosphere: alto-stratus at 3.9 km MSL (gold, top), OD 1 cirrus at 10 km MSL (green, middle), OD 0.25 cirrus at 10 km (blue 2nd from bottom), and clear sky (black, bottom).....	22
2-5. Comparison of water vapor data from TMF (initial analysis conducted by Gavin Lommatsch at MSU).....	25
2-6. A flowchart of the ICI data processing procedure. Currently atmospheric data (including precipitable water vapor) and surface meteorology come from supporting instruments.	26
2-7. Dr. Joseph Shaw with the original ICI at Barrow, Alaska (April 2004) Photograph provided by Joseph Shaw.....	27
2-8. ICI system similar to those deployed to study Earth-space optical Communication.....	29
2-9. The ICI3 instrument during its deployment in Barrow, AK. The exterior paint on the instrument has been worn by the harsh Arctic environment.	30
2-10. The dome all-sky ICI uses an aluminum dome to reflect the whole sky into a FLIR PathFindIR LWIR camera. The off-axis position of the camera is to avoid blocking the zenith sky (photo by Joe Shaw).	31
2-11. Example sky radiance image (left) and cloud attenuation image in dB (right) from the prototype 4 th -generation ICI.	32

LIST OF FIGURES - CONTINUED

Figure	Page
3-1. The ICI3 instrument (foreground) during its deployment at the ARM NSA site in Barrow, AK. Many of the other support instruments located at the ARM site are also shown in the image. (photo by Joe Shaw).....	48
3-2. The ARM NSA site showing the ICI3 and the other co-located instruments. (photo by Joe Shaw).....	49
3-3. ICI3 interior with the control electronics on the left and the camera bay on the right containing the rotating LWIR camera and blackbody.....	53
3-4. The ICI3 exterior with the flip hatch and sliding hatch open, revealing the port for the camera to view the sky.....	54
3-5. ICI electronics rack containing the computer, display, blackbody controller and two RAID external hard drives providing 1TB of redundant storage.	57
4-1. All components of the radiometric input to the camera. Detected signal is a combination of optical power from the detector, substrate, camera body, lens, and scene.....	65
4-2. The output from the ICI3 camera viewing six blackbody scenes while the camera FPA temperature changed: a) blackbody and FPA temperatures; b) varying camera output; c) camera output vs. FPA temperature at six different blackbody temperatures showing both gain and offset changes; and d) change in camera gain vs. FPA temperature for the same six blackbody temperatures.	67
4-3. Heat transfer model of a microbolometer showing the detector connected to the substrate through a conductive junction with conductance of G_s	68
4-4. Microbolometer simulation results showing: a) the blackbody and camera FPA-temperature inputs; b) the varying output from the simulated camera; c) simulated output vs. FPA temperature for six blackbody temperatures; and d) changes in the simulated camera response vs. FPA temperature for six blackbody temperatures. Note that this simulation replicated the trends observed with the measurements from the real camera shown in Figure 4-2.	72

LIST OF FIGURES - CONTINUED

Figure	Page
4-5. Flow Chart of the MSU Photon camera calibration method used in the ICI3. The camera was first stabilized in temperature, then a gain and offset radiometric calibration was applied.	76
4-6. Flow chart of the blackbody-adjusted calibration method that incorporated the blackbody calibration source onboard the ICI3 using 24 hours of blackbody images.....	78
4-7. Blackbody and camera FPA temperature for the 2012 calibration data.....	80
4-8. Plot of the average digital value without FPA-temperature-dependent stabilization with time (a) and with FPA-Temperature (b). These data are from the 2012 calibration data set.....	80
4-9. Plot of the calibration results showing the blackbody temperature (blue), derived blackbody temperature using the FPA-temperature dependent calibration (red), and derived temperature without compensating for FPA temperature (yellow).....	81
4-10. Histogram of the resulting derived blackbody radiance errors without FPA-temperature-dependent stabilization (a) and with FPA-temperature dependent stabilization (b). Note the x axis is over a much smaller range for the corrected data.	82
4-11. The derivation of the best estimates of the ICI3 responsivity: (a) the response of the FTIR directly viewing blackbody target (blue) and through the ICI lens (red); (b) normalized transmission of the lens; (c) Photon detector and filter (no lens) response best estimates; and (d) total spectral response of the FLIR Photon with the IEM lens.....	84
4-12. Genetic-algorithm-derived spectral response (red) with the mean FTIR-estimated ICI response (blue). The genetic-algorithm-derived response deviated from the FTIR-estimated response at wavelengths shorter than 10 μm . Both show significant response outside of the atmospheric window and had similar uncertainties.	86

LIST OF FIGURES - CONTINUED

Figure	Page
4-13. Histogram of the full frame derived NER (a) and NETD (b) and the NER and NETD with a 15-frame average (c) and (d), as in the standard operating mode of the ICI3 during the ARM NSA deployment.....	90
4-14. Variation of the NER across the imager's FPA. This is due to a constant noise power across the FPA but a decrease in radiance from the scene near the edges due in part to the $\cos^4$ roll off that occurs near the edge of the field of view.	91
4-15. Using the Sun as a heating source for the checkerboard pattern. Black squares heat up more, producing a checkerboard pattern in the LWIR. For the calibration presented here, halogen and heat lamps were used rather than the sun.	94
4-16. Sub-set of images used to solve a series of equations to calculate the lens parameters. Regionally dependent gray level conversion from 14 to 8 bits was performed to maximize contrast for data processing.	95
4-17. The field of view map for the ICI3 camera: (a) the zenith angle; and (b) the azimuth angle, assuming that the optical axis of the camera was pointed at the zenith and the bottom of the camera was pointed north.	97
4-18. Field of view uncertainty maps for the ICI3 camera based on the re-projection 3σ error: (a) uncertainty in the zenith angle; and (b) uncertainty in the azimuth angle.	98
5-1. The coefficient of the NSA atmosphere radiance model calculated for zenith angles from 0° to 80°	105
5-2. Reitan relationship between precipitable water vapor and dewpoint temperature for the ARM NSA site derived from radiosonde data (blue circles and red line) and the microwave radiometer (red dots and green line).....	107
5-3. Direct optical depth retrieval based on the logarithm of the cloud residual radiance.	112

LIST OF FIGURES - CONTINUED

Figure	Page
5-4.	The ICI direct cloud detection method. It is important to note the sky radiance and clear sky images have different scales to show the change with angle observed in the clear sky emission. 115
5-5.	The adaptive cloud detection method which assumes errors may exist in the sky radiance or simulated clear sky radiance. 117
5-6.	Diagram of the Almuqantar scan (blue) and zenith angle or Airmass scan (yellow) in the ICI images. 119
5-7.	The support-vector-machine-based cloud detection method. 125
5-8.	The hand-selected cloud (blue dots) and clear sky (red o's) data used as training data shown in 3D scatter plots for three features at a time. The total dataset had 12 features. 129
6-1.	The standard data processing flow for the cloud detection process with the three main sources of uncertainty identified: the camera calibration (red outlined box), the simulated sky imagery (blue box), and the cloud detection thresholds (brown box). 136
6-2.	Detecting the difference between a zero-mean Gaussian random variable and a nonzero-mean Gaussian random variable with the same variances. Clouds with a residual radiance similar in size to the uncertainty in the system (a) and (b) cannot be reliably detected. As the signal-to-noise increases, reliable detection of the cloud increases. 141
6-3.	The atmosphere environment experienced by the ICI3 during deployment at the NSA site: (a) near surface air temperature and (b) precipitable water vapor. 143
6-4.	The Monte Carlo atmospheric radiance uncertainty model for three zenith angles ($\theta = 0^\circ$, $\theta = 20^\circ$, and $\theta = 40^\circ$) over the expected range of air temperature and precipitable water vapor arising from (a) radiance uncertainty in the air temperature measurement and (b) uncertainty in the precipitable water vapor measurement. 144

LIST OF FIGURES - CONTINUED

Figure	Page
6-5. Example application of the atmosphere uncertainty model. (a) Radiance uncertainty for 1000 random pairs of precipitable water vapor and air temperature experienced during the NSA deployment and (b) the radiance uncertainty across the FOV experienced for a specific measurement.	145
6-6. The Monte Carlo radiance uncertainty model based on $\pm 1^\circ$ random errors caused by misalignment of the ICI system. Note the impact of the error increases with zenith angle.	146
6-7. Example application of the field of view uncertainty model: (a) uncertainty for 1000 random pairs of surface temperature and air temperature experienced during the NSA deployment and (b) the uncertainty across the FOV experienced for a specific measurement.	147
6-8. The environment experienced by the IC13 LWIR camera: (a) camera FPA temperature and (b) rate of FPA temperature change.	149
6-9. (a) The estimated radiance uncertainty with the difference between FPA self-emission and scene radiance $\sigma_s(\Delta L, dT/dt)$ for two different rates of FPA temperature change and (b) the calibration bias based on rate of FPA temperature change.	150
6-10. The estimated extrapolation-based uncertainty with scene radiance α_e based on the range of scenes experienced during the Barrow AK deployment.	151
6-11. The calibrated radiance uncertainty that results from the uncertainty in the genetic-algorithm-derived spectral response.	152
6-12. Uncertainty in the images caused by changes that occur during a FFC: (a) histogram of the differences between blackbody images before and after a FFC and (b) the RMS value of the uncertainty across the focal plane array.	153
6-13. Two difference images from different FFC periods on the same day. In (a) the FFC period had a scene of thick clouds and the noise was low and uniform. In (b) the FFC period had a changing scene of thin clouds and clear sky and the noise showed distinct banding.	154

LIST OF FIGURES - CONTINUED

Figure	Page
6-14. Direct optical depth retrieval based on the logarithm of the cloud residual radiance, showing the uncertainty-equivalent-cloud optical depth method, where the best-fit cloud was found by the best-fit line and the lower and upper range by the OD range estimate.	158
7-1. The percent change in gain and offset between the during-deployment first week calibration and during-deployment last week.	169
7-2. The percent change in gain and offset between the pre-deployment calibration and post deployment calibration. Water droplets on the lens can be seen to have left a permanent mark even after the lens was cleaned.	170
7-3. The Atmospheric Emitted Radiance Interferometer at the ARM Southern Great Plains Site; the ARM NSA site has a similar instrument. (Photo from arm.gov).	171
7-4. The differences in the AERI integrated radiances using the different spectral responses estimated by the genetic algorithm for the ICI3.	173
7-5. Data from the complete deployment of the ICI3 using the standard 2016 calibration with no adjustments from the ICI3 on-board blackbody.	175
7-6. Data from early in the ICI3 deployment for all four data calibrations. The 2012S and the two blackbody-adjusted calibrations follow the AERI data best.	176
7-7. Data from the middle of the ICI3 deployment for all four data calibrations. At this point the 2012 standard calibration no longer tracked the AERI, but the 2016 standard calibration did. The two blackbody-adjusted calibrations also followed the AERI data.	177
7-8. Data from near the end of the ICI3 deployment for all four data calibrations. The 2016 standard calibration and two blackbody adjusted calibrations tracked the AERI data at this time.	177

LIST OF FIGURES - CONTINUED

Figure	Page
7-9. The difference between the AERI and the ICI3 data using both the 2016 standard and the 2016 blackbody-adjusted data. These data started with a wide difference, but quickly converged after the 2012-2013 winter. The blackbody did not operate at the start of 2013.....	178
7-10. The difference between the AERI and the ICI3 data using both the 2012 standard and the 2012 blackbody adjusted data. These data started with a small difference, but the 2012 standard calibration degraded during the 2012-2013 winter.	179
7-11. Scatter plot (a) and difference histogram (b) for the AERI and ICI3 data over the entire ARM NSA deployment using the 2016S ICI3 calibration.	180
7-12. Scatter plot (a) and difference histogram (b) for the AERI and ICI3 data over the entire ARM NSA deployment using the 2016S ICI3 calibration.	180
7-13. Scatter plot (a) and difference histogram (b) for the AERI and ICI3 data over the entire ARM NSA deployment when using the Band 51 calibration.	181
7-14. The 2016 Best Calibration scatter plot (a) and histogram (b). The region circled in red in panel (a) is 24 hours of bad data that occurred when the camera rotation mount locked up. These data were replaced with the 2016S data during instrument comparisons.....	183
7-15. The negative residual radiance in blue, and its reflection across zero in red for two different processing methods: (a) direct physics, (b) gradient-and-time adaptive algorithm using a three-frame history.	185
7-16. Time series of four different data processing routines over a 36-hour period selected for high variability. The figure shows the 2016S with the direct processing (v1) and the adaptive v4 processing along with two of the SVM outputs.....	187
7-17. Time series of four different data processing routines over a 36-hour period selected for high variability. The figure shows the 2016S with the direct processing and the adaptive v4 processing along with two of the SVM outputs.	188

LIST OF FIGURES - CONTINUED

Figure	Page
7-18. Example photos of the three passive instruments that were installed at the ARM NSA site (a) the TSI, (b) the MFRSR, and (c) the SKYRAD. These photos are of similar instruments located at ARM SGP (photos from arm.gov).....	189
7-19. Example photos of the two active instruments that operated at the ARM NSA site during the ICI deployment (a) the CEIL and (b) the MPL, these photos are from similar instruments installed at ARM SGP (photo from arm.gov).	189
7-20. Scatter plot of TSI versus CEIL cloud fraction (a) histogram of the cloud difference (b).....	193
7-21. Scatter plot of MFRSR versus CEIL cloud fraction (a) histogram of the cloud difference (b).....	194
7-22. Scatter plot of SkyRad versus CEIL cloud fraction (a) histogram of the cloud difference (b).....	195
7-23. Scatter plot of MPL versus CEIL cloud fraction in the 500m AGL to 7.6 km AGL region of cloud-detection overlap.....	196
7-24. Scatter plot of MFRSR versus TSI cloud fraction (a) histogram of the cloud difference (b).....	197
7-25. Scatter plot of SkyRad versus TSI cloud fraction (a) histogram of the cloud difference (b).....	198
7-26. Scatter plot of MFRSR versus SkyRad cloud fraction (a) histogram of the cloud difference (b).....	199
7-27. Scatter plot of ICI3 versus TSI cloud fraction (a) histogram of the cloud difference (b).....	204
7-28. Scatter plot of SkyRad versus ICI cloud fraction (a) histogram of the cloud difference (b).....	205
7-29. Scatter plot of MFRSR versus ICI cloud fraction (a) histogram of the cloud difference (b).....	206
7-30. Scatter plot of ICI versus CEIL cloud fraction (a) histogram of the cloud difference (b).....	207

LIST OF FIGURES - CONTINUED

Figure	Page
7-31. The non-radiometric ICI3 SVM1 versus the CEIL showing good comparison as seen the scatter plot (a) and difference histogram (b).....	208
7-32. The non-radiometric ICI3 SVM2 versus the CEIL showing good comparison as seen in the scatter plot (a) and difference histogram (b).....	208
7-33. Cloud Fraction at ARM NSA as measured by the ARM cloud instruments in terms of sky coverage.....	210
7-34. Smile diagrams showing cloud fraction occurrence at ARM NSA measured by the ICI3. The top row shown the radiometric data processing for both TSI match time periods (a) and all time periods (b). The middle row shows the non-radiometric SVM version 1 data processing for both TSI matched time periods (c) and all time periods (d).	211
7-35. The ICI3 higher cloud detection versus the CEIL. The ICI v4 L3 (decreased cloud radiance threshold) is more sensitive to thin clouds.	213
7-36. The ICI3 higher cloud detection versus the TSI. The ICI v4 L3 (decreased cloud radiance threshold) is more sensitive to thin clouds.	213
7-37. The ICI3 higher cloud detection versus the Max Active Cloud. The ICI v4 L3 (decreased cloud radiance threshold) is more sensitive to thin clouds.....	214
7-38. The ICI3 higher cloud detection versus the Max Active Cloud. The ICI v4 L3 (decreased cloud radiance threshold) is more sensitive to thin clouds.....	214
7-39. The monthly average cloud fraction for the increased-cloud-sensitivity ICI3 data with level 4 standard sensitivity in blue, and level 3 high sensitivity in yellow.	215
7-40. The monthly average cloud fraction for the increased-cloud-sensitivity-LIDAR data and standard CEIL data in blue, and Max Active Cloud in yellow.	215

LIST OF FIGURES - CONTINUED

Figure	Page
7-41. The monthly cloud fraction difference between ICI3 level 3 high sensitivity data and the level 4 standard sensitivity data.	216
7-42. The monthly cloud fraction difference between Max Active Cloud high sensitivity data and the CEIL standard sensitivity data.	216

GLOSSARY OF ACRONYMS

AERI – Atmospheric Emitted Radiance Interferometer

AON – Arctic Observing Network

ARM – Atmospheric Radiation Measurement

ARSCL – Active Remotely-Sensed Cloud Locations

ASIVA – All Sky Infrared Visible Analyzer

ASTIC – The Blue Sky Imaging All Sky Thermal Infrared Camera

CEIL – Ceilometer

CRF – Cloud Radiative Forcing

ETL – Environmental Technology Laboratory

FOV – Field Of View

FPA – Focal Plane Array

FTIR – Fourier Transform Infrared spectrometer

GPS – global positioning system

ICI – Infrared Cloud Imager

ICI1 – First-Generation Infrared Cloud Imager

ICI2 – Second-Generation Infrared Cloud Imager

ICI3 – Third-Generation Infrared Cloud Imager

ICI4 – fourth-generation ICI

IFOV – Instantaneous Field of View

IPCC – Intergovernmental Panel on Climate Change

JPL – Jet Propulsion Laboratory

GLOSSARY OF ACRONYMS - CONTINUED

LIDAR – LIght Detection And Ranging

LWIR – Long-Wave InfraRed

MATLAB – MATrix LABoratory

MFRSR –Multi-Filter Rotating Shadowband Radiometer

MODTRAN – MODerate resolution atmospheric TRANsmission

MPL – the Micro-Pulse Lidar

MSL – Mean Sea Level

MSU – Montana State University

MWR – MicroWave Radiometers

NASA – National Aeronautics and Space Administration

NEC – Noise-Equivalent Cloud

NER – Noise Equivalent Radiance

NETD – Noise Equivalent Temperature Difference

NOAA – National Oceanic and Atmospheric Administration

NSA – North Slope of Alaska

NUC – Non-Uniformity Correction

OD – Optical-Depth

ORSL – Optical Remote Sensor Laboratory

PWV – Precipitable Water Vapor

RADAR – Radio Detection And Ranging

RASICAM – Radiometric All-Sky Infrared Camera

GLOSSARY OF ACRONYMS - CONTINUED

RBF – Radial Basis Functions

RMSE – Root Mean Square Error

SBDART – Santa Barbara Discrete Ordinate Atmospheric Radiative Transfer code

SHEBA – Surface Heat Budget of the Arctic

SGP – Sothern Great Planes

SKYRAD – Sky Radiometers for Downwelling Radiation

SNR – Signal to Noise Ratio

SVM – Support Vector Machine

SVM1 – Support Vector Machine algorithm 1

SVM2 – Support Vector Machine algorithm 2

TEC – Thermo-Electric Cooler

TMF – Table Mountain Facility

TSI – Total Sky Imager

UEC – Uncertainty Equivalent Cloud

UPS – Uninterruptible Power Supply

VAP – Value Added Product

WSI – Whole Sky Imager

WSIRCMS – Whole-Sky Infrared Cloud-Measuring System

ABSTRACT

Cloud cover is an important but poorly understood component of current climate models, and although climate change is most easily observed in the Arctic, cloud data in the Arctic is unreliable or simply unavailable. Ground-based infrared cloud imaging has the potential to fill this gap. This technique uses a thermal infrared camera to observe cloud amount, cloud optical depth, and cloud spatial distribution at a particular location. The Montana State University Optical Remote Sensor Laboratory has developed the ground-based Infrared Cloud Imager (ICI) instrument to measure spatial and temporal cloud data. To build an ICI for Arctic sites required the system to be engineered to overcome the challenges of this environment. Of particular challenge was keeping the system calibration and data processing accurate through the severe temperature changes. Another significant challenge was that weak emission from the cold, dry Arctic atmosphere pushed the camera used in the instrument to its operational limits. To gain an understanding of the operation of the ICI systems for the Arctic and to gather critical data on Arctic clouds, a prototype arctic ICI was deployed in Barrow, AK from July 2012 through July 2014. To understand the long-term operation of an ICI in the arctic, a study was conducted of the ICI system accuracy in relation to co-located active and passive sensors. Understanding the operation of this system in the Arctic environment required careful characterization of the full optical system, including the lens, filter, and detector. Alternative data processing techniques using decision trees and support vector machines were studied to improve data accuracy and reduce dependence on auxiliary instrument data and the resulting accuracy is reported here. The work described in this project was part of the effort to develop a fourth-generation ICI ready to be deployed in the Arctic. This system will serve a critical role in developing our understanding of cloud cover in the Arctic, an important but poorly understood region of the world.

CLOUDS ON EARTH

Introduction

Clouds are an ever-present feature of the planetary body on which we live; in short, Earth is a cloudy planet. Clouds have a cooling impact on climate of the Earth by reflecting short-wave solar energy, thereby reducing energy reaching the ground and cooling the surface. Clouds have a warming impact on climate by absorbing and re-emitting long-wave thermal energy back toward the ground, thereby increasing longwave energy at the ground and warming the surface (Bennartz et al. 2013; Morrison et al. 2011; Verlinde et al. 2007). The balance between these two competing effects is called cloud radiative forcing (CRF). When positive, the net effect is to warm the surface; when negative, the clouds have a net cooling effect (Sedlar et al. 2010). Total cloud cover and CRF are, therefore, two critical variables in models used to understand Earth's current and future climate (Ramanathan et al. 1989). Cloud radiative effects can cause widely varying results in climate models (Tjernström et al. 2008); however, cloud effects are some of the least understood components of current climate models.

The climate of the Arctic is changing at a rate more than twice the rate of the global average (Verlinde et al. 2007), and changing faster than current models predict (Interagency Arctic Research Policy Committee 2007). This is in part because the climate in this region is strongly sensitive to cloud cover and CRF (Bennartz et al. 2013; Shupe & Intrieri 2004). This sensitivity is in part owing to the amplified role clouds play in positive CRF, which is the primary source of heating in the Arctic (Vavrus 2004), and in

part owing to the dry atmosphere and high surface albedo (Curry et al. 1996). Previous studies have shown the CRF feedback to be positive throughout the year, except for a short period of negative CRF during mid-summer (Sedlar et al. 2010; Shupe & Intrieri 2004; Intrieri 2002; Schweiger & Key 1994; Curry & Ebert 1992). Thus, in this region clouds provide the largest feedback term in the Arctic radiation budget.

In the Arctic and Antarctic regions, where clouds have some of the greatest impact on climate, clouds and their associated annual cycle tend to be poorly understood (Wyser 2005; Town et al. 2007; Chan & Comiso 2013). Cloud data in the arctic is hampered by limitations imposed by the environment, which can lead to sparse data sets. During the dark winter, satellites looking down struggle to distinguish the cold white clouds from the cold white ice and snow (Chan & Comiso 2013). Observations looking up from the ground often rely on visible cameras or human observers, which have insufficient light to see clouds during the dark winter (Hahn et al. 1995). Comparisons between satellites and ground observations have at times agreed no better than random guessing (Town et al. 2007). This leads to Arctic cloud models that have low correlations with observations (Tjernström et al. 2008).

This need was addressed in the 2007 report of the Intergovernmental Panel on Climate Change (IPCC), which notes that the scarcity of observation hampers understanding of the feedbacks involved in sea ice change, and calls for improved atmospheric observations, specifically of clouds (Solomon 2007). Since the 2007 report, our confidence in the feedbacks driven by clouds has not improved sufficiently, as stated in the 2013 IPCC report on the physical science basis for climate change: “Clouds and

aerosols continue to contribute the largest uncertainty to estimates and interpretations of the Earth's changing energy budget" (Stocker 2014). With these continued uncertainties, there is a need to study further the feedback mechanisms of clouds and their relationship with climate, in particular in the Arctic and the Antarctic, where the magnitude of the feedbacks is the greatest. To address the need for improved climatological data in the Arctic, the National Science Foundation founded the Arctic Observing Network (AON). Within this program was a call for measurements of cloud spatial and radiative properties (ADI Task Force 2012).

This need for improved cloud data in the Arctic has been addressed by my PhD work described in this dissertation. My approach has been to use the Third-Generation Infrared Cloud Imager (ICI3), a thermal imaging sensor similar to those used on satellites, but based on a low cost microbolometer camera and looking up from the ground. The ICI3 views thermal emission from the clouds, which provides adequate contrast to isolate the cloud signals from the thermally colder clear sky. When combined with accurate characterization and computer vision algorithms, the ICI3 can see clouds even during the total darkness of the Arctic winter. As part of my work, the ICI3 was deployed at the northernmost point of the United States in Barrow, Alaska. The instrument ran from July 2012 through July 2014, building a nearly complete 2-year record of Arctic clouds and their optical properties. This deployment produced an accurate set of data for a particular location, which can be compared with and used to improve climate models or satellite data. These data have been analyzed to build an understanding of the accuracy of the ICI3 and similar cameras as cloud-detection

systems, and to provide the information required to build a new system even better suited to Arctic extremes. In future deployments these sensors may become part of a network of sensors covering the Arctic to fill a gap in our current understanding of the sensitive Arctic climate and provide a better understanding of the future climate of our planet (Interagency Arctic Research Policy Committee 2007; ADI Task Force 2012).

Methods of Collecting Cloud Cover Data

There are a wide variety of cloud detection methods, including but not limited to Earth-observing satellites, LIDARS, RADARS, human observers, radiometers, and imagers. These instruments tend to agree in terms of trends, but there are statistically significant differences between the cloud fractions measured by various instruments, particularly in the Arctic and Antarctic (Wyser 2005; Town et al. 2007; Chan & Comiso 2013).

Measurements of cloud cover typically are provided in terms of cloud fraction and cloud optical depth. Cloud fraction is defined as the percent of sky area covered with clouds. Cloud optical depth (dimensionless) is the path-integrated extinction experienced by light propagating through a cloud, and is a function of wavelength.

The ideal instrument to measure cloud cover needs to provide continuous data day and night, with both high spatial (or angular) and temporal resolution. Data produced by the instrument need to classify clouds by optical depth. Although there are many methods of detecting cloud cover, most current methods have been designed to fit a particular need and do not meet all these requirements.

Earth Orbiting Satellites Satellite imagery can provide worldwide cloud coverage data (Wojcik et al. 2005) from both emitted and scattered light (Stephens & Kummerow 2007). These capabilities come with natural limitations and a trade-off between spatial and temporal resolution. Satellites in geosynchronous orbit provide continuous data, but at lower spatial resolution. Satellites in near-Earth orbits provide images with higher spatial resolution, but only once or twice per day (Platnick et al. 2003). In the Arctic and Antarctic, this problem is enhanced because the absence of sunlight in the winter makes cloud-detection methods based on scattered sunlight impractical. In the emissive bands, cold clouds produce a low radiometric contrast against the cold, ice-covered surface, leading to underestimation of cloud cover during the arctic or Antarctic winter (Chan & Comiso 2013).

Surface Observations by Human Observers Surface observations performed by trained human observers provide long-term information of cloud coverage for a number of specific sites throughout the world (Piazzolla & Slobin 2002). However, nighttime observations by human observers are difficult because of thin clouds through which stars can be seen (Hahn et al. 1995). This is particularly true during the Arctic and Antarctic winter, where surface observations have been shown to be unreliable at best, and statistically no better than random guessing at worst (Town et al. 2007).

Lidars and Radars Continuous observations with high accuracy can be achieved by ground-based Radio Detection and Ranging instruments (RADARs) and Light Detection and Ranging instruments (LIDARs). These instruments typically rely on time series of zenith data to infer spatial cloud statistics (Moran & Martner 1998; Clothiaux &

Ackerman 2000; Campbell & Hlavka 2002; Intrieri & Shupe 2002) which miss clouds that do not cross the zenith during a data collection period. The temporal and spatial covariance becomes equal when the observation time is long compared with the transport time, (Taylor 1938) and in these cases the zenith data can be assumed to be an accurate measure of the total cloud fraction. The required time period is driven by the wind speed and direction at the cloud altitude. When applied to clouds, this may not hold true over short time periods or in regions where local geography impacts the spatial distribution of clouds (Thurairajah & Shaw 2005). It is such high-temporal-resolution data that are used to compare with climate model calculations.

Ground-Based Radiometers Ground-based radiometers avoid the problems with zenith measurements by measuring the direct and scattered solar irradiance across different regions of the sky with different radiative paths and across multiple bandwidths (Hodges & Michalsky 2011; Stoffel 2004). These instruments are primarily used to derive the atmospheric optical depth (Hodges & Michalsky 2011) and total radiative energy exchange (Stoffel 2004). However, analysis of the shortwave and longwave flux measurements from these instruments can be used to determine periods of clear skies, (Long & Ackerman 2000) provide an estimated total sky cloudiness, (Long et al. 2006) and with advanced processing provide estimates of cloud optical depth (Long 2004). These methods all depend on the presence of direct or scattered solar irradiance and only operate during daylight. This inhibits these instruments from operating during the long night of the polar winter.

Ground-Based Imagers Ground-based imagers avoid the problems with measurements that are restricted to the zenith. These imagers often measure clouds over the entire sky dome (Slater et al. 2001). Such measurements have been shown to agree with a nadir-viewing satellite cloud fraction for full-angle fields of view out to 100° (down to 50° from the zenith). At larger angles, the observation of sides of clouds causes an overestimate of the total cloud cover (Kassianov 2005). Ground-based sky imagers historically operate in the visible spectrum and often rely on red/blue ratios of skylight to identify clouds (Long et al. 2001). This causes problems when trying to identify clouds at night or at times near sunset or sunrise. High-sensitivity imagers using star maps also have been used at night (Shields & Karr 1998); however, the use of different day and night cloud-retrieval methods produce biases between the day and night data sets (Thurairajah & Shaw 2005). Such a bias can become a significant problem during the long nights of the Arctic and Antarctic winters.

Motivation for a Ground-Based Infrared Cloud Imager

The need to study cloud cover over long continuous periods encompassing both day and night led to the development of the Infrared Cloud Imager (ICI) by Dr. Joseph Shaw during his time at the National Oceanic and Atmospheric Administration (NOAA) Environmental Technology Laboratory (ETL) with funding by the Japanese Communications Research Laboratory. The ICI systems are ground-based long-wave infrared (LWIR) imagers that image the sky, remove the atmospheric emission, and process the remaining signal to detect and classify clouds (J. A. Shaw et al. 2005;

Thurairajah & Shaw 2005; Shaw & Nugent 2013; Nugent et al. 2013; Nugent et al. 2009; Nugent 2008). The ICI instruments provide more than just another method of detecting cloud cover data; rather, they have been designed to provide continuous day and night cloud measurements using a consistent cloud-detection method. These instruments have been motivated by the impact of clouds on climate, where clouds drive radiative forcing (Thurairajah & Shaw 2005; J. Shaw et al. 2005), and the impact of clouds on Earth-to-space optical communication channels (Nugent et al. 2013; Nugent et al. 2009), where clouds act as attenuators. In both of these applications, information about total cloud cover, cloud optical depth, and cloud spatial distribution are required and can be provided by the ICI systems.

The Barrow Alaska Data Set

In 2011, the Optical Remote Sensor Laboratory (ORSL) at MSU received a grant to develop an understanding of the operation of an ICI in the Arctic for future deployments as part of the National Science Foundation's Arctic Observing Network (AON). As part of this research effort, a third-generation ICI, the ICI3, was deployed at the Department of Energy Atmospheric Radiation Measurement (ARM) Program's North Slope of Alaska (NSA) facility near Barrow, AK, from July 2012 through July 2014. This deployment was designed to demonstrate the ability of the ICI3 instrument to operate in the arctic and to produce a long-term data set characterizing Arctic clouds, with the ICI3 operating next to a wide variety of other cloud sensing research instruments.

This deployment has created one of the longest-running datasets of LWIR cloud-imager measurements in the Arctic. The only other similar examples were the Surface

Heat Budget of the Arctic (SHEBA) project, in which a suite of atmospheric sensors were operated from a Canadian ice breaker frozen into the pack ice from September 1997 to November 1998 (Intrieri & Shupe 2002; Intrieri 2002; Wyser 2005) and more recent multi-year deployments at a facility high on the Greenland ice sheet (Shupe et al. 2013; Bennartz et al. 2013). Data from our Alaska deployment have become a significant contribution to the arctic cloud science community, and now published and publicly available as part of the ARM database. This data set includes the following cloud data products:

- Horizontal cloud fraction (% of sky filled with clouds) & spatial distribution;
- Cloud optical depth for thin clouds with an optical depth less than three;

This unique data set has also been used to study the operational accuracy of the ICI instruments and has led to an understanding of the true operational accuracy of these instruments in the Arctic. This analysis includes both comparisons with other instruments and an analysis of the uncertainties present in the ICI3 and their impact on data products. The ARM NSA facility was well suited to this project because of the number of co-deployed instruments that produce cloud data products with well documented processing routines and accuracies. Some of these instruments produced similar data products as the ICI3, although limited to certain angles, such as the zenith, or certain time periods, such as daytime. ICI3 data have been compared with various combinations of data from these co-deployed instruments to determine the operating accuracy of the ICI3 under different conditions. This analysis has been used to validate the ICI3 data processing routines and

has aided the development of improved data processing routines, one of which removes all dependence on data external to the ICI.

Organization of the Following Chapters

The balance of this dissertation is organized in the following manner. Chapter 2 provides background on infrared cloud imaging, including its basic principles, a discussion of the work conducted by the ORSL at MSU, and a discussion of parallel work conducted elsewhere. Chapter 3 provides a description of the ICI3 instrument deployed to Barrow AK. Chapter 4 describes the calibration process and provides an analysis of the calibration accuracy of the instrument. Chapter 5 provides a description of the cloud data processing routines used by the ICI3. Chapter 6 contains a careful analysis of the uncertainties present in the ICI3 data and their impact on the resulting cloud data. Chapter 7 provides a careful analysis of the cloud data collected at Barrow, AK, describing both the data provided by the ICI3 and the similarities and differences of the ICI3 data in comparison with data from co-deployed instruments. This analysis includes a radiometric comparison between the ICI3 and other co-located instruments with overlapping spectral responses. Chapter 8 concludes this dissertation by discussing the lessons learned during the ICI3 deployment in Barrow, AK and next steps that need to be taken to further develop these systems.

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INFRARED CLOUD IMAGING

Infrared Cloud Imaging

The first ground-based, longwave infrared cloud monitoring system was pioneered by Christian Werner in 1973. He used a single-channel IR thermistor bolometer and a scanning mirror as an automatic indicator of cloud cover (Werner 1973). This instrument proved that LWIR signals could be used as an indicator of clouds from the ground. The first true cloud imager was the Sloan Digital Sky Survey cloud scanner developed in 1994 (Hull et al. 1994). This instrument used a scanning single-channel liquid-nitrogen-cooled HgCdT detector scanned over a $135^{\circ} \times 135^{\circ}$ by two mirrors to build a 300×300 pixel image of the overhead sky. With the declassification in 1992 of the micro-bolometer cameras developed by Honeywell, a revolution in low-cost thermal imaging occurred (Kruse 2001). The availability of LWIR imagers increased and their cost was greatly decreased, allowing for lower-cost imagers enabling applications that previously had been uneconomical such as LWIR cloud imagers.

LWIR imaging is a nearly ideal method of measuring cloud cover because it can provide continual measurements of clouds with consistent sensitivity day or night. The Infrared Cloud Imager (ICI) developed by the Optical Remote Sensor Laboratory (ORSL) at Montana State University (MSU) (Shaw et al. 2005; Thurairajah & Shaw 2005; Nugent 2008; P. W. Nugent et al. 2013; Shaw & Nugent 2013) and other Long Wave Infrared (LWIR) cloud imagers developed by other researchers (Smith & Toumi 2008b; Suganuma et al. 2007; Ahn et al. 2015; Rumi et al. 2015; Sun et al. 2011) and

commercial groups (Klebe et al. 2014; Wauben 2006) have converted this solution into operational instruments. These instruments image the overhead sky in the LWIR, observing the down-welling LWIR radiance from the clouds independent of sunlight. This allows LWIR cloud imagers to provide high temporal and spatial resolution measurements of cloud amount during day and night with a constant algorithm and instrument response. This chapter outlines the basic operating principles of these instruments, provides specifics on the ICI developed at MSU, and provides an overview of the LWIR instruments developed by other groups.

Advantages Over Visible Wavelength Imagers

Visible-wavelength sky imagers, such as the Total Sky Imager (TSI) (Long et al. 2001) or the retired Whole Sky Imager (WSI) (Shields & Karr 1998), utilize red/blue ratios of scattered sunlight to identify clouds (nearly equal blue red content) from clear sky (more blue) during the day, but struggle or simply cannot operate during night or near sunrise or sunset (Long et al. 2006). The WSI has operated through the night by using star maps to identify clouds where stars are obscured (Shields & Karr 1998), but using a different algorithm for day and night cloud detection has been shown to bias the resulting data product (Thuraijah & Shaw 2005). Day-night consistency is the strongest advantage of LWIR imagers. This is important because clouds and associated radiative forcing can have a significant diurnal pattern, which has a major impact on climate model accuracy, as demonstrated by studies using ground-based sensor and satellites (Ellingson & Ba 2003; Stubenrauch et al. 2006; Miller et al. 1998).

The other significant advantage of LWIR imagers over visible imagers is that LWIR imagers can operate without sun occultation. To avoid damage to the camera, visible imagers must block or occult the sun with an opaque disk (Long et al. 2001; Shields & Karr 1998). This results in the removal of useful data in a region of pixels near the sun and often extending across part of the image. However, LWIR imagers can directly view the Sun without damaging the sensor (P. W. Nugent et al. 2013). This advantage is further enhanced by aerosol scattering, which often creates a large bright region near the Sun that must be omitted from data processing with visible images (Klebe et al. 2014). Scattering is wavelength dependent and is greatly reduced to where it can be ignored in LWIR cloud imagers (P. W. Nugent et al. 2013; Shaw & Nugent 2013).

Physics Principles of Longwave Infrared Cloud Imaging

The cameras used in most LWIR imagers, and the ICI systems in particular, have a maximum response from 8 μm to 13 μm , within the 8-14 μm atmospheric window. This spectral region is well suited for ground-based cloud detection because of low atmospheric absorption and emission and the relatively high cloud emission, allowing clouds to be detected against the clear sky. Outside this window there is high absorption and emission from water vapor below 8 μm and water vapor and CO_2 above 14 μm . Figure 2-1 shows example data collected from an ICI deployed at Montana State University (MSU) in Bozeman, MT.

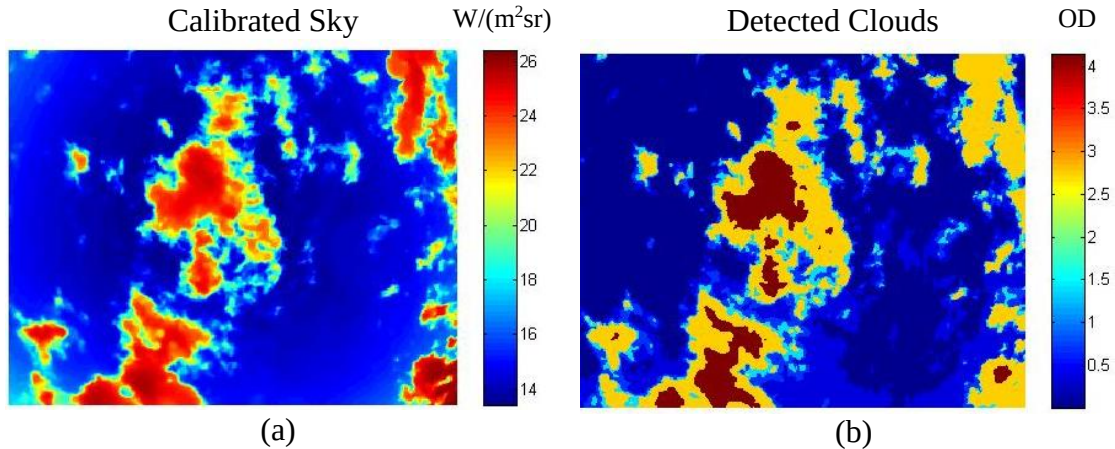


Figure 2-1. Example data taken with a 110° field-of-view ICI showing clear sky (dark blue), thin clouds (light blues) and thick clouds (yellow and red): (a) radiance; (b) cloud optical depth.

The false color image on the right shows the LWIR cloud radiance (red/yellow) above the clear sky (blue). The image on the right shows clouds detected and classified by cloud optical depth, with clear sky shown as dark blue, thin clouds as light blue, and thick clouds as yellow and red. As evident in these images, this spectral region has low but non negligible clear-sky emission; therefore, accurate LWIR cloud imaging systems must compensate for this.

The Atmosphere and Clouds in the LWIR

Clear-air transmission and emission in the LWIR are largely related to the atmospheric water vapor content. To illustrate this, Figure 2-2 and Figure 2-3 show transmittance and emitted radiance in the $8\text{-}14\ \mu\text{m}$ atmospheric window region, according to simulations obtained using MODTRAN atmospheric radiative transfer software (Berk et al. 1999). Figure 2-2 shows a transmittance spectrum of the atmosphere for a zenith path to space for the “1976 U.S. Standard Atmosphere” from an elevation of

2.2 km above sea level, which is representative of Table Mountain, CA, the location of the longest active ICI deployment to date (P. W. Nugent et al. 2013). The simulation was run for two water vapor profiles: the default US76 profile (black line) and the default profile with 1.5x higher water vapor content (red line). Figure 2-3 shows down-welling, clear-sky emission for these two atmospheric models: default US76 (black), and US76 with 1.5x water vapor (red). The emission peak and transmission dip at 9.6 μm are both consequences of ozone (O_3) in the stratosphere.

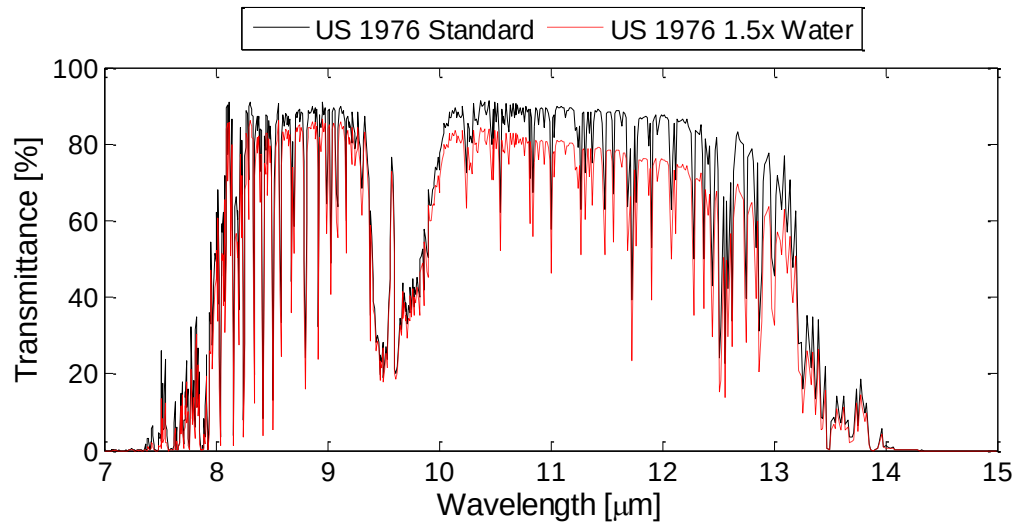


Figure 2-2. Simulated transmittance for the US76 atmosphere (ground level 2.29 km above sea level) with water vapor profiles using default (black) and 1.5x default (red) values.

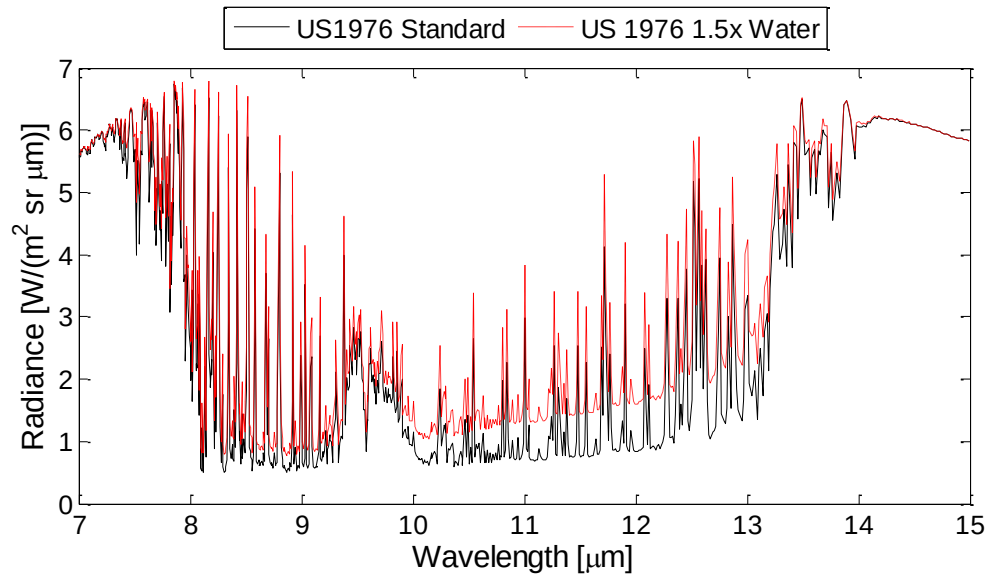


Figure 2-3. Down-welling atmospheric emission spectra for US76 atmosphere with 1.5x default water vapor (red, top), and US76 atmosphere (black, bottom).

Clouds have a higher emission in the LWIR atmospheric window than the clear sky. To illustrate this, Figure 2-4 shows the down-welling spectral radiance when clouds have been added to the US76 atmosphere. Clear-sky emission for a standard 1976 atmosphere is plotted along with emission spectra for three cloud types: low-optical-depth (OD) cirrus clouds at 10 km above mean sea level (MSL) (1 km thick, 550-nm OD = 0.25); cirrus clouds at 10 km MSL (1 km thick, 550-nm OD = 1); and alto-stratus clouds at 4.7 km MSL (0.6 km thick, 550-nm OD = 77).

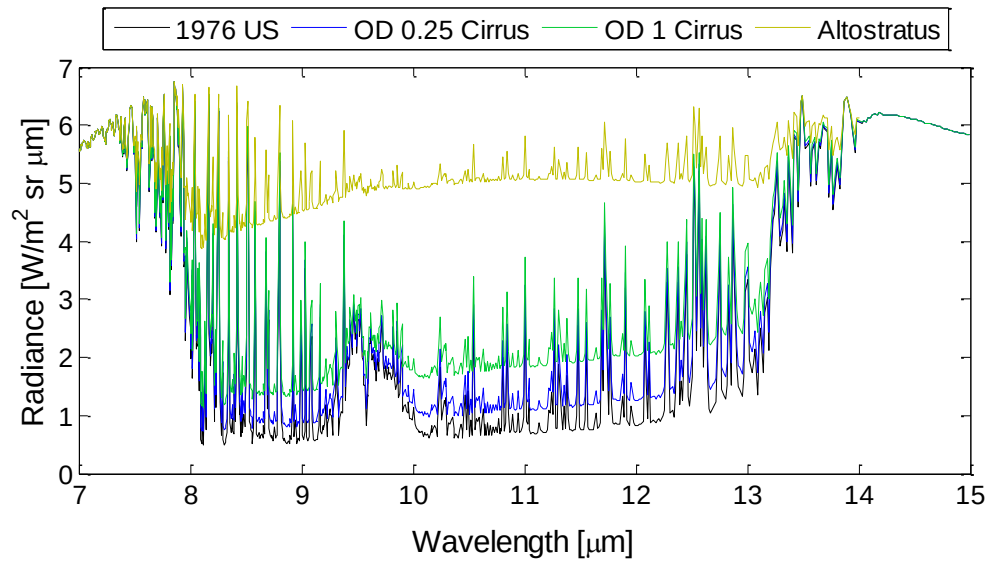


Figure 2-4. Down-welling emission from a cloudy and clear atmosphere: alto-stratus at 3.9 km MSL (gold, top), OD 1 cirrus at 10 km MSL (green, middle), OD 0.25 cirrus at 10 km (blue 2nd from bottom), and clear sky (black, bottom).

As these figures indicate, emission in the 8-14 μm band depends both on atmospheric conditions and clouds, as follows:

- Clear-sky emission arises largely from water vapor, and increases with increased water vapor content;
- There is significant emission from CO_2 , with a peak at 14 μm ;
- Emission from optically thick clouds varies primarily with cloud temperature, which varies with altitude;
- Emission from optically thin clouds depends on the cloud optical depth (OD) and altitude, with optically thin clouds being located typically at higher altitudes with colder temperatures and therefore lower emission.

- Even at the same temperature as the air, clouds emit more than surrounding air because of their higher emissivity (a result of higher absorption in liquid water or ice relative to water vapor and other clear-sky atmospheric gases).

Need for Simulating the Atmosphere

Detection of clouds in the LWIR requires isolation of the cloud signal from the sky background emission. This requires knowledge of and careful removal of the atmospheric emission from the image. Various techniques for this have been proposed, including simulating clear sky emission (Thurairajah & Shaw 2005; Shaw et al. 2005; Shaw & Nugent 2013) or using adaptive methods that use an approximated curve of the clear sky emission to identify cloud-free regions (P. W. Nugent et al. 2013; Smith & Toumi 2008b; Klebe et al. 2014).

In the ICI systems, a model is used to estimate and remove atmospheric emission. The clear-sky radiance is then removed from the calibrated sky radiance and the resulting residual radiance is passed through a cloud detection algorithm. This algorithm in its simplest form is a set of thresholds used to locate clouds. More complicated algorithms will be described in Chapter 5.

Accurate modeling of the atmosphere requires knowledge of atmospheric conditions and surface meteorology at the time the LWIR images were collected. Typically, independent support instruments provide measurements of total precipitable water vapor (PWV), atmospheric temperature profiles, near-surface air temperature, and near-surface dew point temperature. As evidenced in Figure 2-2 and Figure 2-3, the most

critical of these measurements is PWV, as the radiance increase from thin clouds is similar to that of increased PWV.

Measurements of PWV can be derived from a variety of sources, such as solar radiometers (Holben et al. 1998), microwave radiometers (MWR) (Turner et al. 2007), global positioning system (GPS) ground stations (Bevis et al. 1992), and radiosondes (Holdridge et al. 2011). Some of these data are only periodically available; for example, radiosondes are only available when launched and solar radiometers need a cloud-free path to the sun (Holben et al. 1998). Other instruments such as MWR and GPS can provide continuous data, but are not available at all locations. This problem becomes of critical importance at remote locations.

Therefore, to fill in gaps in PWV data, the ICI instruments use the Reitan method (Reitan 1963; Tomasi 1981) to relate the natural logarithm of PWV to the near-surface dew point from ground measurements. In this method, the PWV can be estimated through a first-order polynomial function,

$$\ln(W_p) = aT_{dew} + b, \quad 2 - 1$$

where W_p is the precipitable water vapor, T_{dew} is the dew point temperature (in Kelvin) and a and b are coefficients derived for a specific location. Reitan models are used routinely with ICI systems at locations such as the NASA TMF and the MSU campus in Bozeman, MT, where water vapor data are provided by AERONET solar radiometers (Holben et al. 1998).

Independent of the method used to measure it, the temporal resolution, accuracy, and uncertainty in the supporting data becomes a source of uncertainty in the ICI

instruments. Figure 2-5 shows the variability between three different co-located instruments used to measure PWV at TMF. This uncertainty is a significant challenge facing all LWIR cloud imaging systems, including the ICI systems.

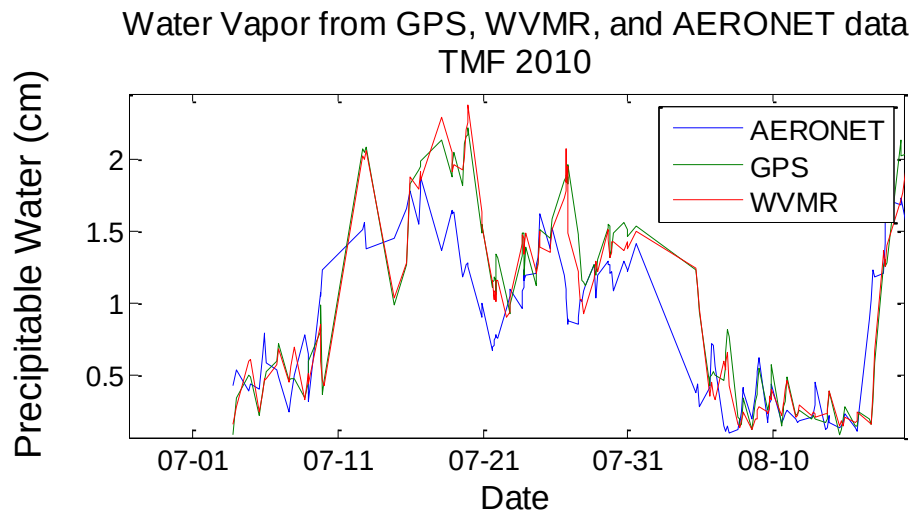


Figure 2-5. Comparison of water vapor data from TMF (initial analysis conducted by Gavin Lommatsch at MSU).

Use of Microbolometer Cameras

The ICI systems and other similar LWIR cloud imagers are based on low-cost, commercial LWIR cameras, which are typically built around microbolometer sensors. These LWIR cameras operate without thermo-electric coolers, and therefore have a digital output that changes with temperature of the camera FPA, lens, and camera body. Calibration algorithms have been developed and deployed on the existing ICI systems to address this difficulty (Paul W. Nugent et al. 2013; Nugent & Shaw 2014). Without such algorithms, the emission from thin cirrus clouds fall well below the camera's operational uncertainty. Accurate calibration becomes critical in the Arctic where the low emission from cold skies and the cold environment push these algorithms to their operational

limits. The calibration procedures and the accuracy achieved during the deployment at the NSA site is discussed in Chapter 4, Chapter 6, and Chapter 7.

The Montana State University Infrared Cloud Imager

The ICI system and method was conceived at the National Oceanic and Atmospheric Administration (NOAA) Environmental Technology Laboratory (ETL) as a ground-based instrument to measure spatial and temporal cloud statistics. Initial testing at deployments in Boulder, CO and the University of Alaska Fairbanks (UAF) Poker Flat Research Range (PFRR) proved the technique could provide accurate measurements of clouds and the LWIR atmosphere (Hilton & Shaw 1999; Shaw 1998). To detect clouds, the ICI images the sky, uses atmospheric models with surface meteorology and PWV measurements to model and remove the atmospheric emission, and processes the remaining signal to detect and classify clouds [9-12]. Figure 2-6 shows the basic ICI data processing procedure.

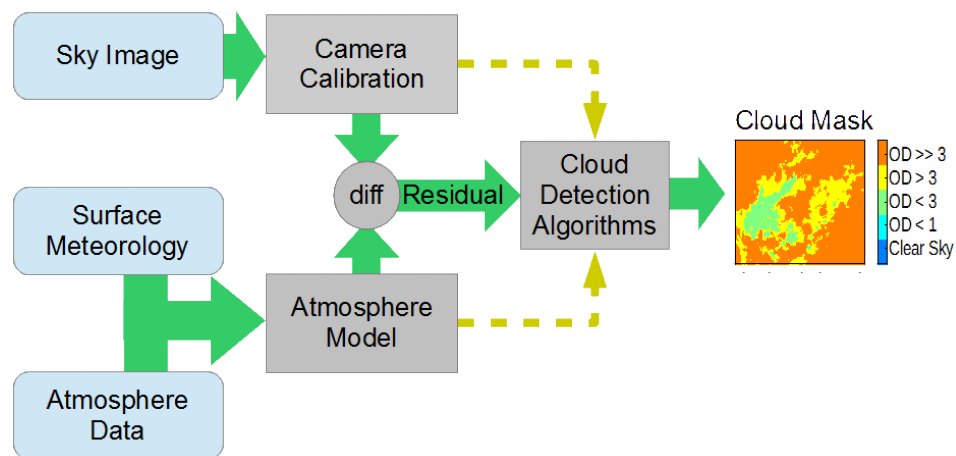


Figure 2-6. A flowchart of the ICI data processing procedure. Currently atmospheric data (including precipitable water vapor) and surface meteorology come from supporting instruments.

The MSU ORSL has further developed the ICI instrument to measure spatial and temporal statistics of clouds for both climate research and Earth-space optical communication path characterization. The following section provides details on the specific versions of the ICI and provides a deployment history of the instruments.

ICI Generation 1

The first-generation ICI instruments were those developed directly out of the work at NOAA/ETL. Those instruments were then transferred to MSU when Dr. Joseph Shaw moved there from NOAA/ETL. These imagers used an Amber Sentinel microbolometer camera and included two onboard blackbody sources for image calibration. This instrument demonstrated the accuracy of LWIR cloud imaging through deployments at Barrow, AK, Lamont, OK, and Poker Flatt Research Range, AK (Shaw et al. 2005; Thurairajah & Shaw 2005). Figure 2-7 shows Dr. Joseph Shaw with the generation-1 ICI at Barrow, AK during its deployment at Barrow in March 2004.



Figure 2-7. Dr. Joseph Shaw with the original ICI at Barrow, Alaska (April 2004)
Photograph provided by Joseph Shaw.

ICI Generation 2

The second-generation ICI (ICI2) was developed at MSU in collaboration with the NASA Jet Propulsion Laboratory (JPL) for cloud studies to understand cloud attenuation in Earth-space optical communication channels. The first two models were built using the FLIR Photon (Anon 2008; Kostrzewa et al. 2005) LWIR camera, but the four latest instruments have used the FLIR TAU2 LWIR camera because the Photon cameras were discontinued (Anon 2015a). This ICI was the first to be deployed without an onboard blackbody source, relying instead on advanced camera calibration techniques (Paul W. Nugent et al. 2013; Nugent & Shaw 2014; Nugent et al. 2014). The camera and associated electronics are housed in an environmentally sealed steel enclosure with a diamond-coated germanium window through which the camera views the sky as opposed to the protective hatch (Paul W Nugent et al. 2009; Paul W. Nugent et al. 2009). Figure 2-8, shows an example mechanical model of the second-generation ICI system. The first model of this ICI has been deployed at the Table Mountain Facility (TMF) in CA July 1 2007 (P. W. Nugent et al. 2013), which houses a number of telescopes dedicated to optical communication [8]. Six distinct units of this instruments have been built and are either deployed or in preparation for deployment at: Goldstone, CA; White Sands, NM; Table Mountain, CA; and the Svalbard Satellite Station near Longyearbyen in Svalbard, Norway.

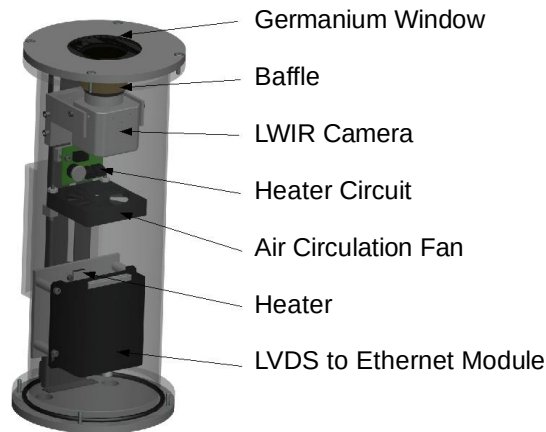


Figure 2-8. ICI system similar to those deployed to study Earth-space optical Communication.

ICI Generation 3

The third-generation ICI (ICI3) was developed as a mix between the first- and second-generation ICI systems. It used the same camera calibration techniques developed for the second-generation cloud imagers (Paul W. Nugent et al. 2013; Nugent & Shaw 2014; Nugent et al. 2014), and it had a single onboard blackbody source, which allowed for long-term studies of instrument calibration. The instrument used a FLIR Photon camera (Anon 2008; Kostrzewa et al. 2005) with an after-market wide field of view lens (Anon 2015b). With this lens the ICI3 has a 110° diagonal field of view, wider than any previous ICI instruments.

The ICI3 was developed to be deployed at the Department of Energy Atmospheric Radiation Measurement (ARM) Program's North Slope of Alaska (NSA) facility near Barrow, AK, where it was deployed from July 2012 through July 2014. This deployment was designed to demonstrate the ability of the ICI instrument to operate in the arctic and to produce a long-term data set characterizing Arctic clouds with the ICI operating next

to a wide variety of other cloud sensing research instruments. Figure 2-9 shows a photo of the ICI3 instrument taken during its deployment at the ARM NSA site in Barrow, AK. This instrument is discussed in great detail in Chapter 3.



Figure 2-9. The ICI3 instrument during its deployment in Barrow, AK. The exterior paint on the instrument has been worn by the harsh Arctic environment.

ICI Dome System

The Dome ICI is a divergence from the traditional ICI instrument designs. This was developed as an experimental instrument through a collaboration with MSU and NASA JPL. This system uses a FLIR PathFindIR LWIR camera to view the sky reflected off an aluminum dome, allowing for an image of the whole sky. This is similar in concept to visible-wavelength cloud imagers that use a reflective dome (Long et al. 2001). However, unlike visible reflective cloud imagers, in the dome ICI the camera was mounted off-axis to allow for comparison with zenith-pointed LIDAR systems and to minimize sky blockage by the camera. Deployment of this instrument at MSU next to the

ICI3 has shown the instrument to be sufficiently accurate to be used in cloud cover studies. Figure 2-10 shows the dome ICI during its deployment next the ICI3 in Bozeman, MT and clearly demonstrates the off-axis design.



Figure 2-10. The dome all-sky ICI uses an aluminum dome to reflect the whole sky into a FLIR PathFindIR LWIR camera. The off-axis position of the camera is to avoid blocking the zenith sky (photo by Joe Shaw).

The Fourth-Generation ICI

The fourth-generation ICI (ICI4) has been designed for the purpose of collecting long-term cloud cover data in the Arctic. Lessons learned from the Barrow, AK deployment of the ICI3 has allowed for an instrument better engineered to handle the challenges of this environment. To maximize the usefulness of the instrument, the system's field of view (FOV) has been increased to 180° , allowing the system to image the entire sky. The 180° FOV prevents the instrument from being deployed with a blackbody reference, as such a blackbody would have to be a full dome, with a prohibitively high cost. Thus this instrument relies on careful calibration and improved

data processing techniques. This instrument is currently in the prototype stage of development, with work focusing on improved data processing and system calibration. Examples of sky radiance and cloud attenuation images measured by this instrument are shown in Figure 2-11. The long-term goal is for this instrument to form the basis of an Arctic cloud imager network to provide the much-needed continuous, high-resolution cloud data in the Arctic.

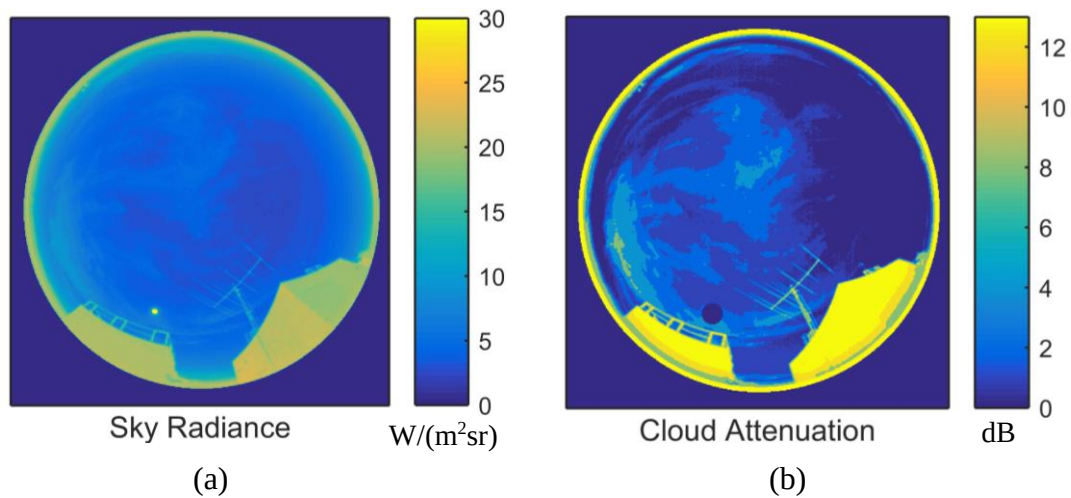


Figure 2-11. Example sky radiance image (left) and cloud attenuation image in dB (right) from the prototype 4th-generation ICI.

A Legacy of Operation

The ICI systems developed by MSU have deployed at a wide variety of sites for both climate research and Earth-space optical communication path characterization. Table 2-1 summarizes the ICI instruments and their deployments. In combination, these deployments encompass over 20 years of instrument operation and associated cloud data. During these multiple field deployments, the instrument has been refined, including the instrument operating procedures and data processing algorithms. These deployments have

provided a history of addressing the challenges associated with long-term field deployments.

Table 2-1. Summary of the ICI deployments

Instrument	Location	Deployment Date
ICI1	ARM SGP in Lamont, OK	2003-02-20 – 2003-04-03
ICI1	ARM NSA in Barrow, AK	2002-02-23 – 2002-05-01
		2004-03-05 – 2004-04-09
ICI1	MSU in Bozeman, MT	2002-10-18 – 2002-12-15
		2004-06-01 – 2005-03-01
ICI1	Poker Flatt Research Range, AK	2005-03-13 – 2006-09-13
ICI2	NASA JPL Table Mountain Facility near Wrightwood, CA	2007-07-01 – Present (with testing at MSU)
ICI2	MSU in Bozeman, MT	2010-11-15 – 2011- 01-27
		2015-06-15 – 2015- 06-27
ICI2	NASA JPL Deep Space Communication Complex in Goldstone, CA	2012-09-04 – Present
ICI2	NASA Glenn in Cleveland, OH	Planned 2016
ICI2	White Sands, NM	Planned 2016
ICI2	Longyearbyen, Svalbard, Norway	Planned 2016
ICI3	MSU in Bozeman, MT	2010-08-09 – 2012-06-27
ICI3	ARM NSA in Barrow, AK	2012-07-13 – 2014-07-22
ICI Dome	MSU in Bozeman, MT	2012-05-18 – 2014-05-02
ICI Dome	NASA JPL in Pasadena, CA	Planned 2016
ICI4	MSU in Bozeman, MT	2015 Summer
		Planned 2016

Other LWIR Imaging Systems

The development and deployment of the first-generation ICI was followed by the development of similar cloud imaging systems by other research institutions (Smith & Toumi 2008b; Suganuma et al. 2007; Ahn et al. 2015; Rumi et al. 2015; Sun et al. 2011) and commercial entities (Klebe et al. 2014; Wauben 2006). This section provides a summary of these instruments and their contribution to LWIR cloud remote sensing.

The All Sky Infrared Visible Analyzer The All Sky Infrared Visible Analyzer

(ASIVA) is a hybrid LWIR / Visible cloud imager developed by the Solmuris Corporation (Sebag et al. 2010; Klebe et al. 2012; Klebe et al. 2014; Tapakis & Charalambides 2013). The ASIVA provides a full 180° fish eye image, and was developed to monitor cloud cover at astronomical installations (Sebag et al. 2010; Klebe et al. 2012). To maximize cloud contrast the instrument uses a selective filter with a 10.2 μm to 12.2 μm band. (Klebe et al. 2012; Klebe et al. 2014) This band is radiometrically calibrated to produce measurements of sky brightness temperature or radiance, with a laboratory measured accuracy of $\pm 0.2 \text{ W}/(\text{m}^2 \text{ sr } \mu\text{m})$ or $\pm 1.4\text{K}$ at 300K.

The ASIVA was deployed at the ARM Southern Great Plains (SGP) facility near Lamont, OK from May 21st through July 28th 2009 as part of the ARM effort to evaluate commercial infrared sky imagers (Klebe et al. 2014; Morris et al. 2011). During this deployment, ASIVA sky images and cloud fraction were found to correlate well with images from the TSI (Morris et al. 2011) when the ASIVA cloud detection threshold was adjusted to reduce thin cloud sensitivity (Klebe et al. 2014). LWIR radiance derived by the ASIVA was shown to agree within 5% of the equivalent band-integrated radiance from the Atmospheric Emitted Radiance Interferometer (AERI) for both cloudy and clear conditions. This instrument is currently deployed at the ARM site in Lamont, OK as the ARM Infrared Sky Imager (Klebe et al. 2015).

The Whole-Sky Infrared Cloud-Measuring System The Whole-Sky Infrared

Cloud-Measuring System (WSIRCMS) is a LWIR cloud imager developed at the College of Meteorology and Oceanography at the PLA University of Science and Technology in

Nanjing, China (Liu et al. 2013; Sun et al. 2011). The WSIRCMS uses an azimuthal scanning station to scan the uncooled LWIR camera to 9 positions to produce an image out to 75° zenith angle (Liu et al. 2013; Tapakis & Charalambides 2013). The WSIRCMS data processing is similar to the ICI, with clouds detected at pixels with radiance significantly higher than that of the clear sky. The radiance of a clear sky is modeled using the Santa Barbara Discrete Ordinate Atmospheric Radiative Transfer code (SBDART), with inputs of surface temperature and PWV. The WSIRCMS was run from July through August 2010 next to a ceilometer. Comparisons showed the WSIRCMS to agree within ± 1 okta in 70.83% of the measurements, where oktas are cloud fraction normalized and rounded to an integer range 0 for clear sky and 8 for fully overcast sky.

In addition to detecting clouds, the WSIRCMS performs a multi-cloud classification algorithm that combines radiance thresholds with a “fuzzy uncertainty texture spectrum” (Sun et al. 2011). This algorithm can classify clear sky and 4 cloud types using textural features (Liu et al. 2011). Comparisons between this cloud classifier and visual inspection on 277 images produced an overall agreement of 90.97% (Sun et al. 2011; Liu et al. 2011).

The Wide Angle LWIR Cloud Imager of Smith and Toumi Stephen Smith and Ralf Toumi at the Imperial College in London developed and deployed a LWIR cloud imager based on a FLIR Thermovision A40 camera (Smith & Toumi 2008b; Smith & Toumi 2008a). The camera was equipped with a lens that gave a 60°×80° field of view. To achieve a zenith to near-horizon image, the camera was tipped so the zenith pixel was near the edge of the field of view. This camera was initially deployed in London during

June 2006 (Smith & Toumi 2008b) and then in Central England at the UK Meteorological Office Research Site in Cardington, Bedfordshire, from 16 February 2007 to 27 April 2007 (Smith & Toumi 2008a).

During the initial deployment they were able to develop a cloud data processing routine that allowed them to operate without any external data by fitting the lowest pixel readings with zenith angle to a curve that described the clear sky. Pixels warmer than the curve fit were classified as clouds (Smith & Toumi 2008b). This fit was able to accurately identify clouds down to 80° from the zenith during periods of partly cloudy sky (Smith & Toumi 2008b). This imager was unable to detect high cirrus clouds, due to difficulty isolating thin clouds from the clear sky using the fitting algorithm (Smith & Toumi 2008b).

During its second deployment, this instrument was used to measure the instantaneous surface Cloud Radiative Forcing (CRF) integrated over $7.5\text{ }\mu\text{m}$ to $13\text{ }\mu\text{m}$. The CRF was calculated using measurements of the cloud fraction, the cloud emission, and the clear sky emission when the sky was not 100% overcast. These measurements showed that CRF was nonlinear as a function of cloud fraction. This nonlinearity was explained by an increase in cloud optical thickness (cloud optical depth) as cloud fraction increased, and that cloud altitude decreased as cloud fraction increased, leading to warmer clouds during times of higher cloud fraction. Comparisons also were made with a co-located ceilometer and to achieve the best agreement the threshold for cloud detection had to be increased (Smith & Toumi 2008a), effectively reducing sensitivity to thin clouds.

The Blue Sky Imaging All Sky Thermal Infrared Camera The Blue Sky Imaging

All Sky Thermal Infrared Camera (ASTIC) is a commercial cloud imager that was deployed at the ARM SGP as part of the Infrared Sky Imager Intercomparison study (Morris 2008; Morris et al. 2011). This imager was developed as a support instrument in the European Union CLOUDMAP2 project (Chapman et al. 2007; Muller & Fischer 2007). This camera was the first to use a thermal fisheye lens to produce full hemispherical cloud cover measurements. The instrument operates on the principle that clouds have a higher brightness temperature than clear sky, and therefore can be detected using a combination of image segmentation and thresholding (Chapman et al. 2007). During the deployment at ARM SGP the ASTIC daytime sky images were found to compare well with TSI images, but the instrument underreported cloud fraction (Morris et al. 2011).

Nubiscope The Nubiscope consists of a single 8-14 μ m LWIR radiometer on a pan/tilt stage that is scanned to build an image of the overhead sky (Wauben 2006; Wauben et al. 2010). This produces an image of the whole sky with angular resolution of 3° in zenith and 10° in azimuth every 6 minutes (Wauben 2006). The Nubiscope was deployed at ARM SGP as part of the Infrared Sky Imager Intercomparison study (Morris 2008; Morris et al. 2011). During this deployment, cloud fraction measurements were found to correlate well with TSI data; however, the 6-min acquisition time for each cloud fraction measurement was determined to hinder the data quality (Morris et al. 2011).

The instrument is one of the few LWIR cloud imagers with reports of its long-term calibration accuracy. The Nubiscope is reported to have a scene brightness

temperature range of -100°C to 50°C and an accuracy of $\pm 0.5^{\circ}\text{C} + 0.7\%$ of the temperature difference between the scene and camera (Wauben 2006). Independent laboratory and field measurements reported the calibration deviation to be $+2^{\circ}\text{C}$ to -0.5°C at $+40^{\circ}\text{C}$ over a period of 2 years (Wauben et al. 2010).

This same study yielded a comparison of data from the Nubiscope and a co-located ceilometer over a full year period. During this study the Nubiscope had identical measurements (same okta) 44% of the time, within ± 1 80% of the time, and ± 2 okta 87% of the time, with an average difference of 0.07 okta, and an absolute deviation of 1.03 okta (Wauben et al. 2010). These differences were stated to be similar with those between the ceilometer and human observers (Wauben et al. 2010).

The Reuniwatt SIONS-T Reuniwatt of France produces a commercial LWIR cloud imager, the SIONS-T. This imager uses a reflective dome to image produce a 180° image of the overhead sky. This imager has been developed to monitor cloud cover and predict cloud attenuation in Earth to Space optical communication channels [11]. Clear sky emission is derived using a function that relates surface dewpoint temperature to clear sky radiance. This instrument derives cloud optical depth based on a cloud type approximation and a curve fit of residual radiance to optical depth [11]. These optical depths, when combined with cloud motion estimates, allow prediction of optical channel interference up to 30 minutes in the future [11].

The Radiometric All-Sky Infrared Camera The Radiometric All-Sky Infrared Camera (RASICAM) is a telescope-based camera that uses two reflective mirrors to allow a LWIR camera to view the full sky in the $10\text{ }\mu\text{m}$ to $12\text{ }\mu\text{m}$ band (Lewis et al.

2010). This camera has been installed in support of the Blanco Telescope located at the Cerro Tololo Inter-American Observatory in Chile. This instrument is primarily used to quantify atmospheric transmission over time in support of the telescopes. This system is unique in that it uses an equi-resolution catadioptric mirror to provide both full sky coverage and to correct for the radiometric increase in observed clear sky with zenith angle due to air mass (Lewis et al. 2010). Data processing for the RASICAM has been extended to include derivation of cloud optical depth (Reil et al. 2014). Similar telescope-based cameras have been installed in support the MAGNUM telescope on Haleakala in Hawaii (Suganuma et al. 2007) and the Subaru telescope on Mauna Kea (Takato et al. 2003). Oceanit sells the MAMBA, a commercial LWIR cloud telescope based on a very similar design (Anon 2016).

Cloud Height from LWIR Imagers

Many of the cloud imagers reviewed in this section derive a cloud height product based on the brightness temperature of the cloud, the surface air temperature, and a lapse rate assumption (Klebe et al. 2014; Sun et al. 2011; Wauben et al. 2010; Morris et al. 2011; Morris 2008; Bertin et al. 2015). This determination is based on the assumption that the cloud acts as a blackbody source. This can be a true approximation for clouds of high optical depth (Lynch et al. 2002), but this is not a general case. In the studies conducted at the ARM SGP site, these cloud height algorithms compared poorly with the Active Remotely-Sensed Cloud Locations (ARSCL) data (Morris et al. 2011). Our routine ICI data processing schemes do not make an independent cloud height measurement.

Cloud Optical Depth from LWIR Imagers

Multiple instruments add cloud optical depth derivation to their standard cloud data processing (Shaw et al. 2012; Paul W Nugent et al. 2009; Suganuma et al. 2007; Bertin et al. 2015; Reil et al. 2014; Lewis et al. 2010). This is done based on the relationship between cloud optical thickness and cloud LWIR emission. For a cloud at a given temperature, cloud emission will increase as cloud optical depth increases. This concept was first suggested with the first LWIR cloud imager produced by the Sloan digital sky survey (Hull et al. 1994), although this technique was not implemented at the time. The specifics of the implementation of cloud optical depth derivation in the ICI cloud imagers is discussed in detail in chapter 5, and results of this algorithm are discussed in chapter 7.

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THE THIRD-GENERATION INFRARED CLOUD IMAGER

Arctic Deployment Site

The third-generation ICI (ICI3) was developed as an instrument to study long-term, year-round cloud cover in the Arctic. In 2011, the Optical Remote Sensor Laboratory (ORSL) at MSU received a grant to deploy an ICI as part of the National Science Foundation's Arctic Observing Network (AON). As part of this research program, the ICI3 was deployed at the Department of Energy Atmospheric Radiation Measurement (ARM) Program's North Slope of Alaska (NSA) facility near Barrow, AK, from July 2012 through July 2014. This deployment demonstrated the ability of the ICI instrument to operate in the arctic, produced a long-term day/night continuous data set characterizing Arctic clouds, and provided much-needed engineering information about the arctic readiness of the ICI systems. The ARM site also allowed for the ICI3 to operate next to a wide variety of other cloud sensing research instruments for demonstrating the capabilities of LWIR cloud imaging in the Arctic.

This deployment has created one of the longest-running datasets of Arctic cloud measurements. Other examples of long-term cloud studies include the Surface Heat Budget of the Arctic (SHEBA) project, in which a suite of atmospheric sensors were operated from a Canadian ice breaker frozen into the pack ice from September 1997 to November 1998 (Intrieri & Shupe 2002; Intrieri 2002; Wyser 2005) and more recent multi-year deployments at a facility high on the Greenland ice sheet (Shupe et al. 2013;

Bennartz et al. 2013). Except for the ICI3, there are no other long-term Arctic cloud studies that included continuous cloud imaging through both the winter and the summer.

Figure 3-1 shows a photo of the ARM site from the perspective of the ICI3. The photo was taken by Dr. Joe Shaw during the ICI3 deployment at the ARM NSA site in Barrow, AK. Figure 3-2 shows the ICI3 in the background with the suite of other ARM instruments in the foreground. In these figures, many of the other support instruments located at the ARM NSA facility can be seen, including cloud radars, radiometers, the Atmospheric Emitted Radiance Interferometer (AERI), the Total Sky Imager (TSI), the Microwave Water Vapor Radiometer (MWR), and the Multi-Filter Rotating Shadowband Radiometer (MFRSR). This deployment presented a unique opportunity to demonstrate the accuracy of LWIR cloud imaging by comparing with the wide variety of other cloud instruments at the site. These comparisons are discussed in detail in Chapter 6. The data from this deployment have become a valuable contribution to the arctic climate research community and have been made publicly available on the ARM archive.



Figure 3-1. The ICI3 instrument (foreground) during its deployment at the ARM NSA site in Barrow, AK. Many of the other support instruments located at the ARM site are also shown in the image. (photo by Joe Shaw).

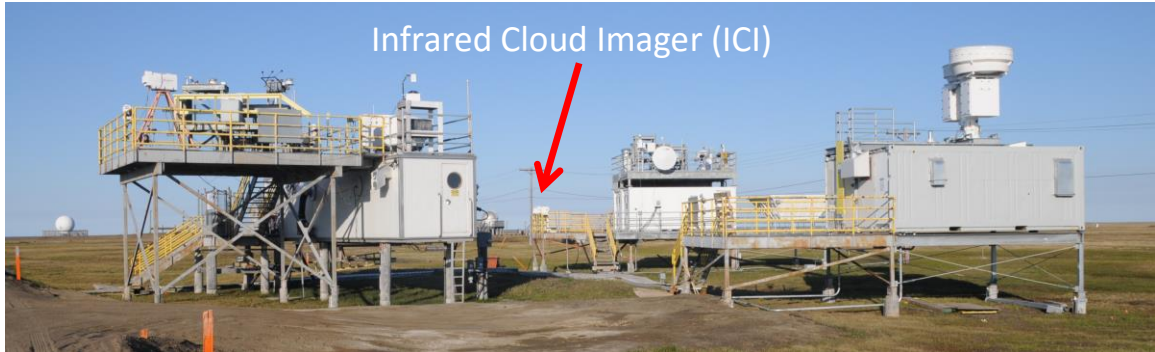


Figure 3-2. The ARM NSA site showing the ICI3 and the other co-located instruments. (photo by Joe Shaw).

Instrument Design

The ICI3 was developed with a deployment to the ARM NSA facility in mind, based on lessons learned from the ICI1 deployment there in 2005 (Thurairajah & Shaw 2005; J. A. Shaw et al. 2005). Deployment in the arctic required the system to be engineered to handle challenges that included the need for remote monitoring and control of the instrument, the ability to run autonomously for extended periods of time, and the ability to operate during harsh Arctic weather. The harsh weather of the Arctic includes cold temperatures, high winds, blowing snow and ice, and salty air from the nearby Arctic Ocean. In particular, the system calibration and data processing needed to be capable of maintaining accuracy through the severe cold temperatures experienced during the Arctic winter.

The ICI3 instrument is split into an external optics enclosure and an internal electronics rack. The optics enclosure contains the LWIR camera, blackbody calibration source and associated electronics. The electronics rack contains the computer that runs the instrument, blackbody power supply, and data archiving RAID hard drives.

Continuity with Previous Instruments

The ICI3 was designed as a hybrid between the Arctic-ruggedized ICI1 and the compact, cost-effective ICI2. To allow the ICI3 to operate in the arctic, it borrowed the well-insulated design of the ruggedized enclosure from the ICI1 (Thurairajah & Shaw 2005; J. Shaw et al. 2005). The enclosure has a hatch that opens to allow the camera to view the sky (J. A. Shaw et al. 2005; Thurairajah & Shaw 2005), as opposed to the germanium window used in the ICI2 systems (Nugent et al. 2009). From the ICI2, the ICI3 took the advanced data processing and calibration techniques that allow these systems to operate without an onboard blackbody (Nugent et al. 2013; Nugent & Shaw 2014; Nugent et al. 2014). However, to test the accuracy of these calibrations over long time periods, the ICI3 incorporated a single onboard blackbody source that could be used for real-time calibration measurements throughout the deployment.

The Optics Enclosure

The ICI3 optics enclosure is a custom-built, all-aluminum enclosure with an overall size of $66 \times 66 \times 42$ cm. This enclosure was a 65% reduction in volume from the ICI1. To allow for safe handling, stainless steel handles were placed on two sides of the instrument. The top of the enclosure was attached by four stainless steel latches so it could be removed to allow access to the interior of the instrument. The enclosure has 3.8 cm of expanded polystyrene foam insulation with an approximate R-value of $1.14 \text{ m}^2\text{K/W}$ (Anon 2015a) on all exterior walls, floor, and the roof. This insulation was insufficient for the winter at ARM NSA. To keep the camera bay within the desired temperature

range, the instrument had to be wrapped in additional insulation and additional heaters were added inside of the camera bay.

The enclosure interior was split between an electronics bay and a camera bay. The two bays are separated by an interior wall. This wall isolated the camera bay, which contained the thermal camera and blackbody, from stray thermal emission produced by the support electronics. The two bays and the internal separation can be seen in Figure 3-3. The enclosure included a PID temperature controller that controls a TEC heater/cooler to keep the temperature of the camera bay near 20 °C. Supplemental heaters had to be added to keep the temperature of the enclosure near 20 °C during the Arctic winter. The internal walls of the camera bay were coated with Krylon 1602, a white spray paint with a published long-wave emissivity of 0.95 (Anon 2016). The inside of the camera bay included temperature and humidity sensors whose data were incorporated into the camera calibration algorithms. The electronics bay included all of the control electronics, motors, data logging, and communication electronics. The electronics bay also included an Ethernet switch that allowed all communication to take place through a single Gigabit Ethernet connection.

The Optical System

The core of the ICI3 optical system was the same camera as the ICI2, the FLIR Photon 320×240 microbolometer camera (Anon 2008; Kostrzewa et al. 2005). The original 14.25 mm lens was replaced by an 8.6-mm, F/1.4 lens (Anon 2015b) that provided the system with a 64°×82° or 107° diagonal field of view (FOV). With this lens, the ICI3 had a wider FOV than any previous ICI instrument (but smaller than the 180°

FOV of the ICI4 prototype). This camera had a spectral response between approximately 8 μm and 14 μm . The specifics of this responsivity, the camera field of view and the calibration of this camera are covered in detail in Chapter 4.

To study the calibration of this camera over time, a LWIR blackbody manufactured by Electro-Optical Industries was housed within the camera bay (Anon 2000). This blackbody provided a 15.2×15.2 cm micro-grooved surface with an emissivity of 0.992. During normal operation, an in situ calibration of the camera was performed by constructing a least-squares linear fit to the band-integrated source radiance and the camera's digital number output. The equation for this linear fit provides the two basic calibration parameters of gain (slope of the line) and offset (zero-radiance intercept of the line). The blackbody temperature was changed every 4 hours over a range of 10 °C to 60 °C in steps of 10 °C. This allowed a unique blackbody-based calibration offset to be calculated for each 4-hour set, or a unique gain and offset to be calculated every 24 hours after a full set of blackbody images with temperatures from 10 °C to 60 °C was obtained.

To fully fill the camera's field of view, the blackbody surface needed to be 7.9 cm from the lens of the camera. This short distance prohibited the placement of a rotating mirror between the camera and blackbody to alternate the view between the sky and the blackbody source, as had been done in the ICI1. Therefore, a camera rotation mount was designed and built to rotate the camera to alternately view the blackbody and the sky. The mount had an off-center rotation that allowed the camera to raise the lens to within 3 mm of the top of the enclosure to avoid clipping of the FOV. A counterweight offset the torque of the camera. Optical position sensors were used to position the rotation mount in

a home position viewing the blackbody, and to position the camera's view at the sky.

Figure 3-3 shows the ICI3 interior. The control electronics are shown on the left, with the camera bay on the right, which contained the rotating LWIR camera and blackbody.

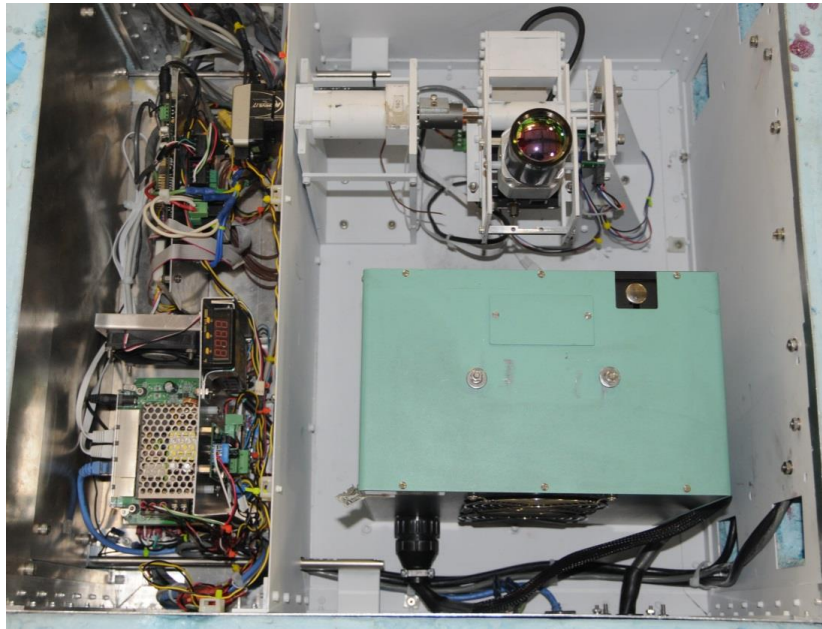


Figure 3-3. ICI3 interior with the control electronics on the left and the camera bay on the right containing the rotating LWIR camera and blackbody.

Hatch System

The ICI3 enclosure used a dual hatch system. The first was a sliding hatch that opened to let the camera view the overhead sky without any obstructing windows, then closed after each image had been collected. The second was a flip hatch that closed during periods of detected precipitation to prevent the sliding hatch from collecting large amounts of snow and to provide an option to cover the camera port in the case that the sliding hatch became jammed with ice. Figure 3-4 shows the ICI3 exterior with the flip

hatch and sliding hatch open. When both hatches were open, the port through which the camera viewed the sky could be seen.

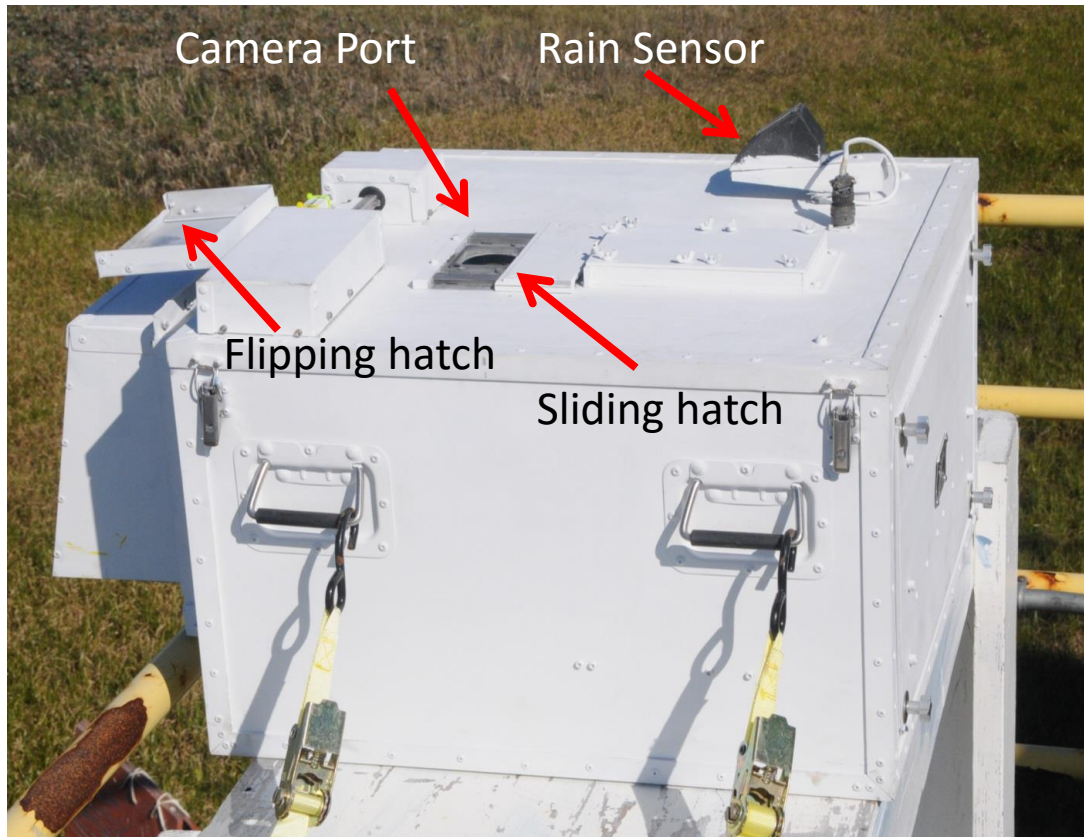


Figure 3-4. The ICI3 exterior with the flip hatch and sliding hatch open, revealing the port for the camera to view the sky.

The sliding design allowed the hatch to have a low profile and not obscure any portion of the camera's wide-angle field of view. It also allowed the hatch to open and close with one rotation direction of the motor. This was intended to reduce mechanical strain and wear during deployment.

The full closed-open-closed cycle for the hatch takes five seconds if using the 12 rpm version of the motor. With an estimated one additional second to collect an image, the hatch was open for six seconds. When operating at one-minute acquisition periods, as

was done in the ARM NSA deployment, this led to the hatch being open 10% of the time. This could lead to significant cooling of the camera relative to the rest of the camera bay, and could lead to temperature gradients developing across the camera lens. These gradients possibly led to additional uncertainty in the camera radiometric calibration (discussed in chapter 5) that was not accounted for in this body of work.

When the hatch was closed during precipitation, there was no cloud measurement data. Historically it had been assumed these periods were fully cloudy with a cloud fraction of one with a high cloud optical depth greater than four. Work conducted at ARM NSA suggests that this may lead to an overestimation of cloud fraction over long time periods.

Internal Microcontroller

The ICI3 incorporated a microcontroller to control and monitor analog and digital sensors and to interface with serial peripheral devices in the instrument. The ICI3 software interface sent commands to the microcontroller through an Ethernet interface. This microcontroller also managed the position of the camera and the open and close state of the hatch. During periods of precipitation, the microcontroller placed the instrument into a standby state and signaled the computer of this state. The microcontroller also put the ICI instrument into a standby state with the hatch closed and the camera homed if no communication was received from the computer for 120 seconds. This allowed the instrument to protect the optics and other critical components in the case of a computer failure.

Instrument Communication

All communication with the instrument took place via a single Ethernet interface. Internally this interface was split by a switch to allow communication with the microcontroller and the LWIR camera. The microcontroller added two serial interfaces that were accessed via a pass-through interface. These interfaces were connected through an RS232 interface to the PID controller and a RS485 interface to the camera rotation motor. Since RS485 can be daisy chained, additional devices such as data loggers or digital controllers could be added to this interface.

Computer and Control

The computer that controlled the ICI was a 1U rack-mount computer housed in an instrument rack. This rack also included a slide-out display that could be used to access the computer on site. Two 500-GB RAID hard drives were located in the instrument rack and these drives could redundantly store up to 3 years of cloud images taken every minute. The controller for the blackbody was housed in this rack and communicated with the computer through an RS232 interface.

To allow for remote power control of the ICI3 instrument enclosure, a remote AC power switch controlled via USB was located in the instrument rack. All components of this rack were connected to a power strip connected to the uninterruptible power supply (UPS) unit located next to the instrument. The UPS was required to allow continuous instrument operation through the many short power glitches that occurred at the ARM NSA facility. Figure 3-5 shows a picture of the ICI Electronics Rack shortly after

unpacking at the ARM site. The computer was located at the bottom of the rack, the slide out display at the top, with the blackbody controller and RAID drives located in between.



Figure 3-5. ICI electronics rack containing the computer, display, blackbody controller and two RAID external hard drives providing 1TB of redundant storage.

Real-Time Operation and Software

The operation of the ICI3 is managed by the custom *Run ICI* software. This software manages all ICI instruments except the ICI1. The *Run ICI* software was written in the Matlab software environment and could be run in a compiled or non-compiled mode. During the deployment at ARM NSA, the ICI ran in a non-compiled mode using a

local Matlab license. This allowed for rapid modification of the software to respond to changing situations such as broken rotation motors.

Real-time data processing was provided by this software. Since precipitable water vapor measurements were not available in real time, the Reitan relationship (Reitan 1963; Tomasi 1981) had to be used to estimate precipitable water from surface dewpoint temperature. This produced an estimate of atmospheric emission with a large uncertainty; therefore, the adaptive gradient-based algorithm described in Chapter 5 was used for real-time data processing.

Throughout the deployment at ARM NSA, the computer was managed with the commercial *RAdmin* remote management software. This software package allowed operators in Bozeman to access the computer, download data, make software changes, and to remotely control the instrument (e.g. moving the camera inside the ICI to allow on-site technicians to make repairs).

To allow for stable long-term operation of the instrument, careful memory management had to be implemented in the ICI software. This required careful management of the Matlab memory space so that all variables were pre-allocated and the memory space remained unchanged as much as possible during operation. Otherwise the memory space would fragment within a few days and Matlab would use more and more memory until the system became unusable. To add additional stability to the system, the software was set to restart itself every 24 hours.

Power Systems

All electrical power was supplied to the instrument through a single AC circuit. Internally this circuit was fused and then split off to separate electrical devices. To run most of the digital electronics, this AC source was converted to 12 V and 5 V DC circuits. Table 3-1 through Table 3-3 describe the power draw of the system under both normal operation and maximum current draw.

Table 3-1. Total system power draw

Maximum	Steady State
1340 W	734 W

Table 3-2. Enclosure power draw

Device	Maximum	Steady State
Blackbody	780 W	204 W
Supplemental heater	200 W	200 W
All other electronics	120 W	118 W

Table 3-3. Instrument Rack Power Draw

Device	Maximum	Steady State
Rackmount PC	181 W	160 W
Monitor	20 W	20 W
RAID hard drives	38 W	32 W
Blackbody controller	Included in enclosure	Included in enclosure

Data Output

Cloud data from the Run ICI were saved as separate Matlab data files for each data collection. Data were saved in subfolders for each day, named according to *yyyy-mm-dd* ([4-number year]-[2-number month]-[2-number day]). Filenames were based on the *yyyy-mm-dd_HHMM_SS* format. Each approximately 500 kB file contained the

variables described in Table 3-4. Daily summary files for each day were saved as well, named *yyyy-mm-dd_averages.mat*. This file contained the daily data structure, which had the fields described in Table 3-5.

Table 3-4. Variables saved in each data file

Variable Name	Description
ave	Number of frames averaged for the sky image
bb_temp	Temperature of the blackbody
cambay_temp	Temperature inside the camera bay
cambay_RH	RH inside the camera bay
cloud_amount	Average cloud amount in each data bin in the image
cloud_image	Sky image separated into the different cloud data bins
dB_image	Sky image in terms of cloud dB
elecbay_RH	RH inside the electronics bay
elecbay_temp	Temperature inside the electronics bay
L_sky	Real-time calibrated sky radiance image
last_cal	Date number of the last FFC or NUC correction on the camera
nist_time	Reading of a NIST time server if available
pwv	Real-time estimated precipitable water vapor
rain	True-false reading of the rain sensor
shutter	Structure containing the shutter image and the FPA temperature at the time of the last FFC, and blackbody images both before and after the FFC
sky	Raw uncalibrated sky image
sky_adjust	Slope and offset adjustments that were applied to the realtime atmosphere model (see Chapter 5).
surface_P	Pressure measured by a nearby met station
surface_RH	Relative humidity measured by a nearby met station
surface_T	Near-surface air temperature measured by a nearby met station
surface_TD	Dewpoint calculated using a nearby met station
time	String representing the time the data were collected

Table 3-5. Data saved in the daily summary files

Variable Name	Description
timeseries	Date numbers for each minute of the day, NaN if no data was collected
thin	Cloud fraction with less than 4 dB attenuation
thick	Cloud fraction with greater than 4 dB attenuation
amount	Fraction of the sky covered by any thickness of clouds
attenuation	Average cloud attenuation across the whole sky

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INSTRUMENT CALIBRATION ARED CLOUD IMAGING

Introduction

The core of the ICI3 is the FLIR Photon™ (Kostrzewa et al. 2005) long-wave infrared (LWIR) camera based on an uncooled microbolometer detector. To build a cloud imager around this camera, it had to be fully characterized in a laboratory setting through measurement of a series of camera parameters. The first is the camera's radiometric response, which required measurement of how the radiometric response changed with camera temperature and measurement of the camera's spectral responsivity. The second is the system noise performance. The final critical measurement was the imager field of view. This chapter discusses the details of these calibration measurements. Each section provides the background of the particular calibration methods and basic uncertainties in the calibration. An in-depth exploration of these uncertainties is addressed in chapter 6, which discusses the calibration accuracy that was achieved during the deployment at the ARM NSA site in Barrow, AK. Many of the calibration procedures are dependent on one another, and the following chapter should not be considered a linear derivation of the camera calibration. For example, the radiometric calibration relies on the responsivity or bandwidth calibration, and therefore both must be understood together.

Radiometric Calibration of the ICI Cameras

The Photon camera used in the ICI3 operates without a thermo-electric cooler (TEC) to provide thermal stabilization. TEC-less microbolometer cameras can operate

with similar digital sensitivity and operating range as comparable TEC-stabilized cameras (Kostrzewa et al. 2002; Fraenkel et al. 2006). This move toward TEC-less imaging was driven by a variety of motivations, including: reduction of camera size, instant-on capability, and reduction in power consumption, (Kostrzewa et al. 2005), although many of these factors are not critical to LWIR cloud imaging. In the ICI systems, TEC-less cameras were selected primarily because of their low cost and their ability to operate without cooling either by liquid nitrogen or sterling cycle coolers (Klipstein et al. 2013), which require increased maintenance and can be disadvantageous for deployment at remote locations. For a long-term cloud imager such as the ICI, uncooled imagers are the most practical solution.

Temperature Sensitivity of TEC-Less Cameras

Uncooled TEC-less microbolometers are hindered by a dependence of the camera's output on the temperature of the focal plane array (FPA). Non-uniformity correction (NUC) routines that incorporate the temperature of the FPA can remove the dependence of fixed-pattern noise on FPA temperature; (Cao & Tisse 2014) however, these TEC-less imagers are still limited as a radiometric sensor since the output is dependent on the temperature of the FPA and other components in the camera. Without stabilization of these effects, the ICI3 could not operate as a radiometric cloud imager.

As shown in Figure 4-1, these changes happen because all components of the camera emit LWIR radiation and the detected signal is a combination of emission from the detector substrate, detector, camera body, lenses, atmosphere, and scene, as described by the following equation

$$P_o = \Gamma_t T_l T_f L_t + L_{l,d} \Gamma_l T_f + L_b \Gamma_{b,d} T_f + L_d (R_l \Gamma_{d,l} T_f^2 + R_s \Gamma_{d,s} + R_b \Gamma_{d,b} T_f^2 - 2\pi A_d) + L_{s,d} \Gamma_s. \quad 4 - 1$$

In this equation P_o represents the total optical power on the detector, Γ represents throughput or etendue, T represents transmittance, R represents reflectance, L represents radiance, and A represents area. The subscripts denote the target (t), lens (l), filter (f), camera body (b), detector (d) and substrate (s). The negative term represents the radiant emission from the detector in all directions; however, some of the power is reflected by the substrate, camera body, or lens, some is absorbed, and some leaves the camera through the lens. If the power budget at the detector is based on these assumptions and all terms dependent on detector emission are grouped, the equation can be simplified to

$$P_o = P_t + P_b(T_{body}) + P_l(T_{lens}) - P_d(T_{fpa})[1 - R_s - R_b - R_l] + P_s(T_{sub}). \quad 4 - 2$$

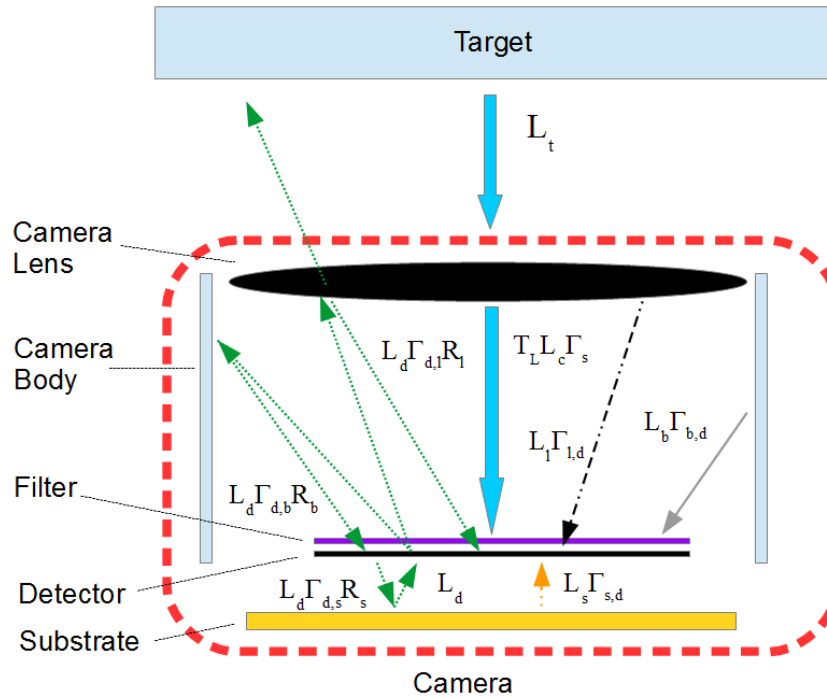


Figure 4-1. All components of the radiometric input to the camera. Detected signal is a combination of optical power from the detector, substrate, camera body, lens, and scene.

Without compensation for these effects, the emission from thin cirrus clouds fall well below the camera's operational uncertainty. Calibration becomes critical in the Arctic where the low emission from cold skies and the cold environment push these algorithms to their operational limits. In the ICI systems, a radiometrically calibrated mode is required to isolate the cloud and clear-sky emission.

Observation with the ICI3 Camera To observe the changes with FPA-temperature in the camera, the ICI3 camera was placed in an environmental chamber while a blackbody source filled the camera's field of view. In the FLIR Photon the FPA-temperature was produced from a temperature sensor embedded in the camera's FPA. The temperature of the chamber was cycled from 20 °C to 40 °C while the blackbody was slowly stepped up in temperature from 10 °C to 60 °C in steps of 10 °C. Images were collected every ten seconds except just after the blackbody temperature was changed, when no data was collected for sixty-minutes while the blackbody to stabilized. The data from this experiment are plotted vs. measurement number in Figure 4-2. Panel (a) shows the blackbody and FPA temperatures. As the camera temperature changed, the camera output also changed, as shown in panels (b) and (c). This is a result of changes in total camera response with both offset and gain changes (c) and changes in the camera gain with FPA-temperature (d).

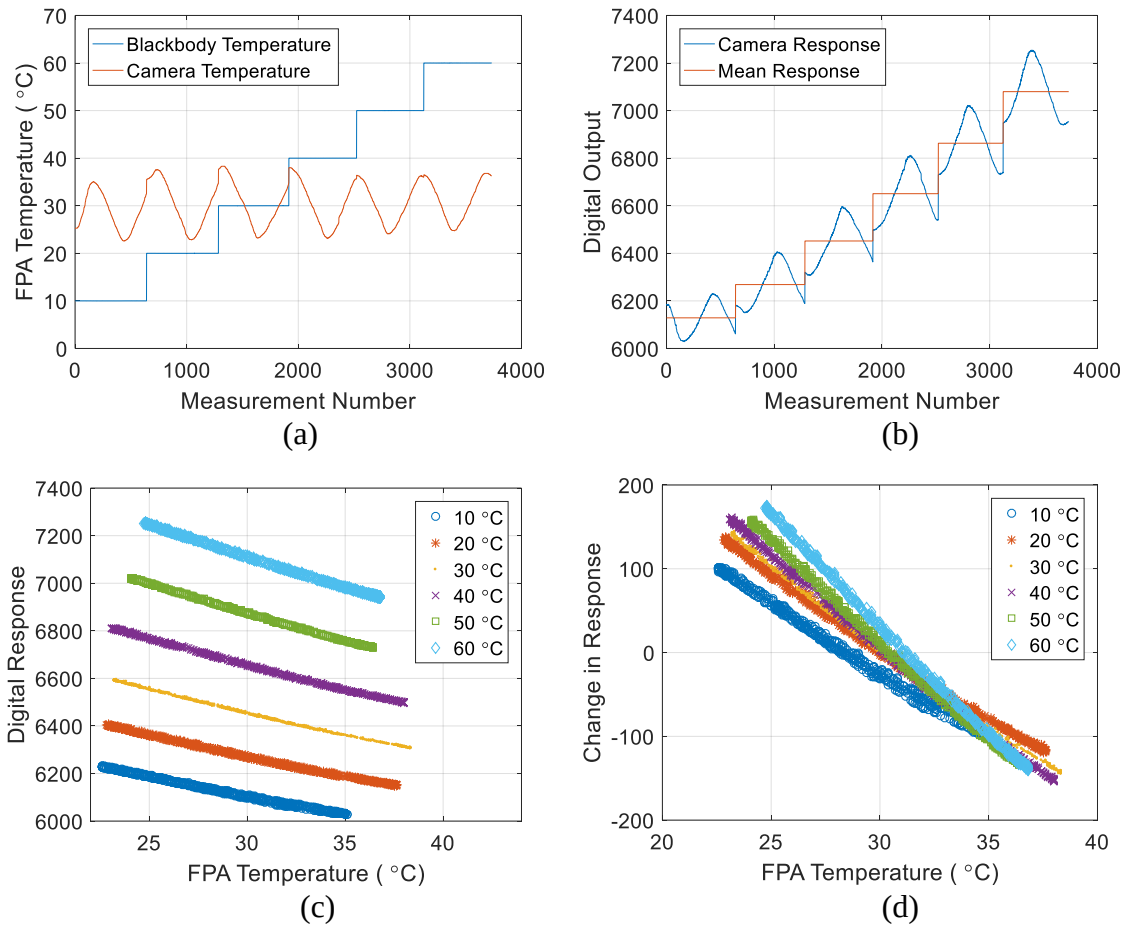


Figure 4-2. The output from the ICI3 camera viewing six blackbody scenes while the camera FPA temperature changed: a) blackbody and FPA temperatures; b) varying camera output; c) camera output vs. FPA temperature at six different blackbody temperatures showing both gain and offset changes; and d) change in camera gain vs. FPA temperature for the same six blackbody temperatures.

Microbolometer Temperature Model To understand the source of these changes, a mathematical model of the microbolometer camera in the ICI3 was built from a variety of published microbolometer models (Xiu-Bao et al. 2010; Hollister 2006; Sui et al. 2010; Waves 2002). Many of these models effectively simulate the dynamic changes in the microbolometer on millisecond scales. This is not the goal of the model developed to understand the ICI3; therefore, this model works in the steady state by allowing the

variable of time t to go to ∞ . For the purpose of this simple model, the transmittance of the lens can be set to 1, as can the transmittance of the filter. We can also assume that the sensor is not band limited and thus the radiances can be estimated by the Stefan-Boltzmann law. In band limited cameras, such as the FLIR Photon, the T^4 relationship changes and often can be described by an exponent between 3 and 4 over limited temperature ranges. For the simplified camera model a non-band limited camera model was used.

This models starts with a simplified heat transfer model of a microbolometer pixel with the detector modeled as a thermal mass connected to the substrate through a conductive junction with conductance of G_s , as shown in Figure 4-3.

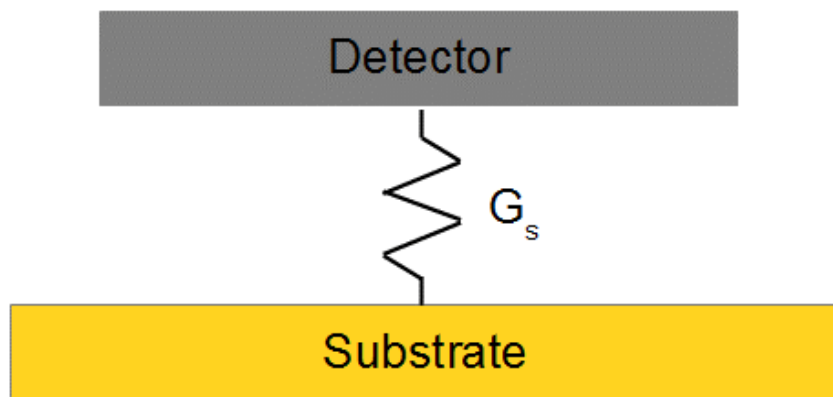


Figure 4-3. Heat transfer model of a microbolometer showing the detector connected to the substrate through a conductive junction with conductance of G_s .

Temperature of the Detector The microbolometer pixels have a resistance that changes based on the temperature of the pixel. The linear function in Eq. (4 - 1) can be used to describe this temperature-dependent resistance, where T_0 is room temperature 300 K, R_0 is the microbolometer pixel resistance at room temperature (20 k Ω for this model),

T is the current temperature of the microbolometer, and α is the temperature coefficient of resistance.

$$R(T) = R_0[1 + \alpha (T - T_0)] \quad 4 - 3$$

The microbolometer pixel will change in temperature in response to the power in the detector W , which is both the optical power P_o and the electrical power P_E ,

$$W = P_E + P_o. \quad 4 - 4$$

The electrical power P_E is a result of the bias current required to read out the microbolometer resistance changes. In current microbolometer cameras, this current is modulated to minimize heating of the microbolometer and P_E is small compared to P_o (Sui et al. 2010). These microbolometers are encased in a vacuum and if microbolometer emission is accounted for in the optical power budget then it can be shown that the thermal conductance G_s , a combination of the of the radiative coupling with the substrate and the conduction through the substrate junction regulates the steady state pixel temperature according to

$$W = G_s(T_d - T_s), \quad 4 - 5$$

where T_s is the temperature of the substrate and T_d is the temperature of the pixel (Vollmer & Möllmann 2010). If this equation is solved for the steady-state detector temperature,

$$T_d = \frac{P_o + P_E}{G_s} + T_s. \quad 4 - 6$$

This model is sufficient to show the offset in microbolometer temperature that takes place as the camera components change temperature. However, it is insufficient to describe the changes in camera gain.

To model the changes in camera gain, the conductance of the mechanical connection G_s must be allowed to vary with substrate temperature. These changes can be described as

$$G_s(T_s) = G_{s0} \left(\frac{T_s}{T_0} \right)^\beta + 4A_d \sigma T_d^3, \quad 4 - 7$$

where the first component describes the conductance through the bolometer leg to the substrate (Hollister 2006), T_0 is temperature at which G_{s0} is measured and β is an exponent that controls how this conductance changes. In this model β tends to control the higher-order curvature of the change in slope. To best replicate the curvature experienced with the Photon camera, a β of 4 was required. This value was much greater than a typical value of 1.7 reported in literature. It is likely this was due to a limitation of the simplified microbolometer model. The second term describes the radiant loss of the detector and is found as the time derivative of the Stefan-Boltzmann equation (Vollmer & Möllmann 2010).

Voltage Output The voltage output of the microbolometer is read by a carefully controlled bias current, leading to a measureable voltage

$$V_o = i_b R(T) = i_b R_0 [1 + \alpha (T_d - T_0)]. \quad 4 - 8$$

To reduce substrate temperature dependence in the voltage output and reduce sensitivity to P_E , microbolometers will incorporate blind pixels that do not have any response to the scene and thus only respond to the camera temperature and the readout current, and will have a temperature T_b described by

$$T_b = \frac{P_E}{G_s} + T_s. \quad 4 - 9$$

In this case, the measured camera voltage V_m becomes

$$V_m = i_b R_0 [1 + \alpha (T_d - T_0)] - i_b R_0 [1 + \alpha (T_b - T_0)]. \quad 4 - 10$$

This equation can be reduced to

$$V_m = i_b R_0 [\alpha (T_d - T_b)]. \quad 4 - 11$$

Inserting the functions of T_d and T_b lead to

$$V_m = i_b R_0 \left[\alpha \left(\left(\frac{P_o + P_E}{G_s} + T_s \right) - \left(\frac{P_E}{G_s} + T_s \right) \right) \right], \quad 4 - 12$$

which can be reduced, canceling both the direct response to the temperature of the substrate T_s and the electrical power from the readout current P_E . Reflected emission from the bolometer remain as does the temperature dependence in the conductance of the mechanical connection to the substrate $G_s(T_s)$. In this case the readout voltage can be modeled by

$$V_m = i_b R_0 \alpha \left(\frac{P_o}{G_s(T_s)} \right). \quad 4 - 13$$

This yields a camera output that increases with increasing scene temperature but decreases as the substrate temperature increases. In this model and in the ICI3 camera, radiative effects dominate the transfer of energy in the microbolometer, which leads to temperature dependence in the offset that is an order of magnitude greater than in the gain. Since the optical power P_o has components that depend on T_d , this model needed to be solved numerically and a simple iterative method proved to be sufficient.

Simulation Results The results of the microbolometer simulation are shown in Figure 4-4. First a simulation was run for a camera with a constant FPA-temperature of 25 °C and the blackbody temperatures from the camera tests shown in Figure 4-2. Then

the simulation was run with a changing FPA-temperature using both the FPA-temperature and blackbody temperature from the actual camera test shown in Figure 4-2. As can be seen in panels (b), (c) and (d), the varying output from the simulated camera compared well with the real camera shown in Figure 4-2. This model was able to reproduce the changes observed in the Photon data as the camera temperature was changed. This included changes in both the camera offset and camera gain.

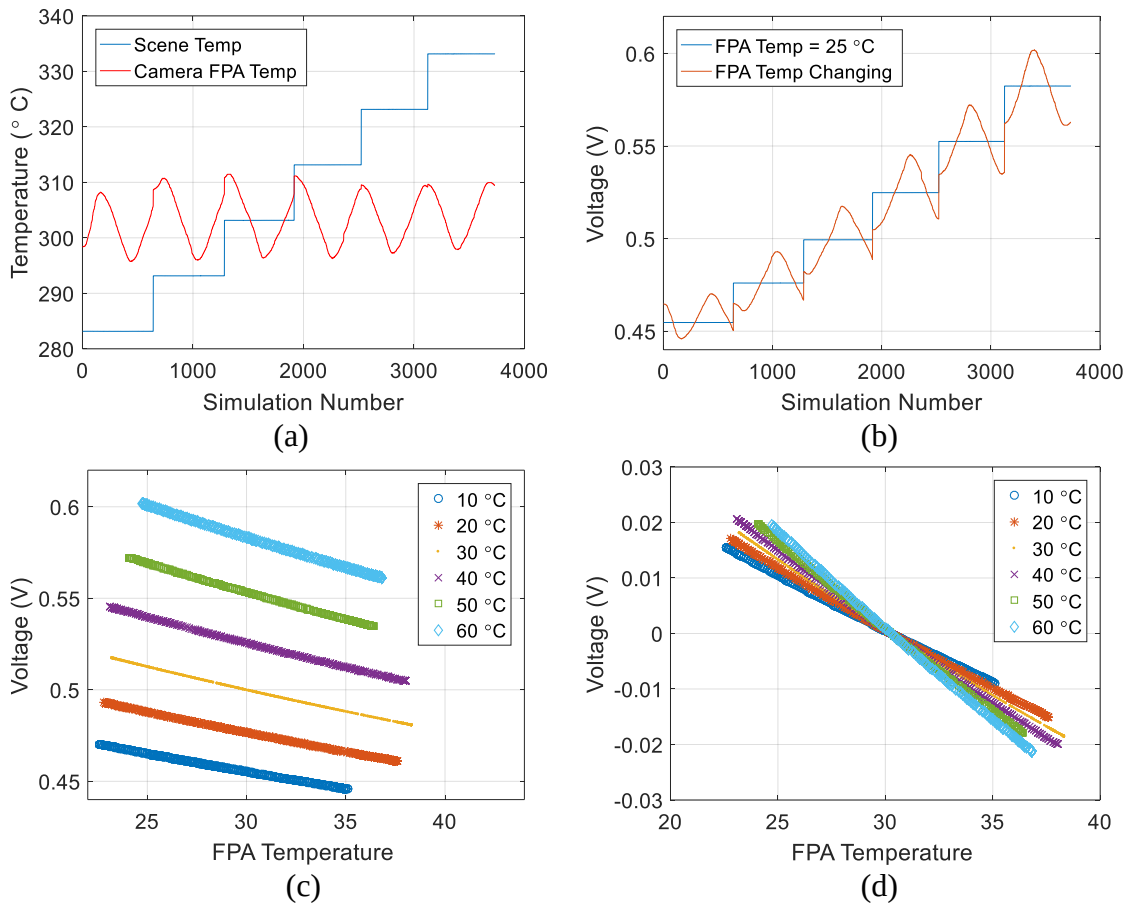


Figure 4-4. Microbolometer simulation results showing: a) the blackbody and camera FPA-temperature inputs; b) the varying output from the simulated camera; c) simulated output vs. FPA temperature for six blackbody temperatures; and d) changes in the simulated camera response vs. FPA temperature for six blackbody temperatures. Note that this simulation replicated the trends observed with the measurements from the real camera shown in Figure 4-2.

Application of Calibration Algorithms

During the deployment of the ICI in barrow, two calibration procedures were used to produce accurate radiometric images of clouds. The first applied a laboratory-derived radiometric calibration measured before and after the deployment. The second used images of the on-board blackbody recorded during the deployment to adjust the laboratory calibration.

Removing FPA Temperature Dependence The first step in the radiometric calibration of the ICI3 was to remove the dependence on the camera temperatures (Nugent et al. 2013; Nugent & Shaw 2014). In the Photon camera used in the ICI3, the only temperature information about the camera elements is the FPA temperature. Therefore, these temperature stabilization routines adjusted the camera output based on readings of the FPA temperature to produce FPA-temperature-independent data. A standard radiometric calibration was then applied to the FPA-temperature-independent data. This made the inherent assumption that all camera elements, the, substrate, camera body, and lens, can all be tracked based on the FPA temperature readings. It did not assume they are the same, only that they are linearly related. This assumption would be invalid when significant temperature gradients developed within a camera element such as the lens. It is expected these gradients will develop due to the difference between the camera temperature and external air temperature (to which the first lens element must be exposed). Therefore, this may be a source of increased calibration uncertainty.

These calibration routines were built before the microbolometer model was developed, and were based on an empirical study of these cameras. However, by using

the model a better understanding of how these routines correct the FPA-temperature dependence has been developed. The digital output of the camera can be described as the scene radiance multiplied by a temperature-dependent gain added to a temperature-dependent offset. This result can be achieved from the microbolometer model by starting with Eq. 4 - 2, the optical power budget for the detector. First, a temperature-dependent self-emission term $P_{self}(T)$ is defined as

$$P_{self}(T) = P_s(T_{sub}) + P_b(T_{body}) + P_l(T_{lens}) \quad 4 - 14$$

and a self-reflected term R_{self} is defined as

$$R_{self} = R_s + R_b + R_l. \quad 4 - 15$$

In this case, the optical power budget is simplified to

$$P_o = P_t + P_{self}(T) - P_d(T_{fpa})[1 - R_{self}]. \quad 4 - 16$$

Adding this term into the equation for output voltage, V_m , yields

$$V_m = i_b R_0 \alpha \left(\frac{P_t + P_{self}(T) - P_d(T_{fpa})[1 - R_{self}]}{G_s(T_s)} \right). \quad 4 - 17$$

This equation can be split into a term dependent on scene (or target) radiance, L_t , and a term that is only dependent on the current camera's temperature:

$$V_m = i_b R_0 \alpha \left(\frac{\Gamma_t T_l T_f}{G_s(T_s)} \right) L_t + i_b R_0 \alpha \left(\frac{P_{self}(T) - P_d(T_{fpa})[1 - R_{self}]}{G_s(T_s)} \right). \quad 4 - 18$$

If digitization is considered, the left-hand term that depends on scene radiance is considered a temperature-dependent gain $G(T)$, and the right-hand term that depends on the current camera temperature is considered a temperature-dependent offset or bias $B(T)$, then the digital output of the camera, D_N , can be described as

$$D_N = G(T)L_t + B(T). \quad 4 - 19$$

From this point, the procedures outlined in the published ICI camera calibration procedures can be followed (Nugent et al. 2013; Nugent, Shaw, et al. 2014; Nugent & Shaw 2014). The result of these published procedures is a temperature correction equation of the following form:

$$D_{Nc} = \frac{D_N - b(\Delta T)}{1 + m(\Delta T)}, \quad 4 - 20$$

where D_{Nc} is the FPA-temperature-corrected digital number, $b(\Delta T)$ is a temperature-dependent bias correction, $m(\Delta T)$ is a temperature-dependent gain correction, and ΔT is the difference between the FPA temperature and a reference temperature of 25 °C. In an extension from the published results, the $b(\Delta T)$ in the ICI3 was described by a polynomial function with three temperature terms and a constant bias o_1 :

$$b(\Delta T) = b_1\Delta T + b_s\Delta T^2 + b_s\Delta T^3 - o_1. \quad 4 - 21$$

The gain term $m(\Delta T)$ for the ICI3 was the same as in previous cloud imagers, and was simply described as a scalar multiplied by the FPA temperature difference:

$$m(\Delta T) = m_1\Delta T. \quad 4 - 22$$

This results in the following digital number correction equation for the ICI3:

$$D_{Nc} = \frac{D_N - b_1\Delta T - b_s\Delta T^2 - b_s\Delta T^3 + o_1}{1 + m_1\Delta T}. \quad 4 - 23$$

This processing was shown to reduce the FPA-temperature dependence in the ICI's TEC-less microbolometer camera by more than 95%. This processing required a unique set of correction coefficients for each of the pixels in the ICI3 camera.

Standard Radiometric Calibration of the ICI3 Data Once the FPA-temperature correction had been applied, a radiometric calibration was applied to produce the

calibrated data required by the standard cloud processing methods. This calibration was based on a linear relationship between FPA-temperature-corrected camera response and scene radiance, resulting in the equation

$$L_{sky} = gD_{Nc} + b, \quad 4 - 24$$

where g is the calibration gain for a camera at 25°C and b is the camera bias at 25°C.

$$L_{sky} = g \left[\frac{D_N - b_1 \Delta T - b_s \Delta T^2 - b_s \Delta T^3 + o_1}{1 + m_1 \Delta T} \right] + b. \quad 4 - 25$$

Similar to the FPA temperature correction coefficients, the parameters g and b were determined uniquely for each pixel in the ICI3 camera. Figure 4-5 shows a flow chart of this radiometric calibration, including the FPA temperature correction.

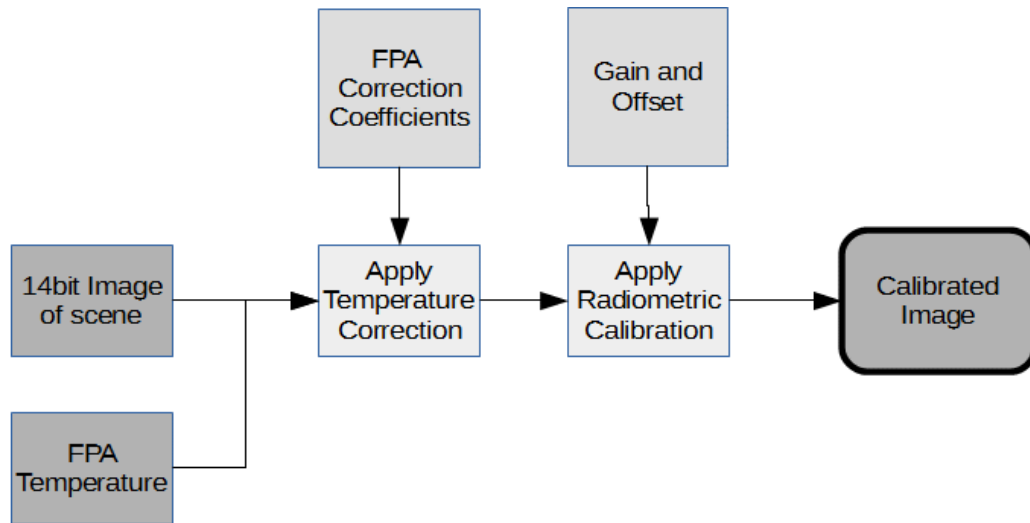


Figure 4-5. Flow Chart of the MSU Photon camera calibration method used in the ICI3. The camera was first stabilized in temperature, then a gain and offset radiometric calibration was applied.

Blackbody-Adjusted Radiometric Calibration During the deployment of the ICI at Barrow, AK, it was possible that the camera calibration could drift away from the

calibration measured in the laboratory. To allow us to study this process and to improve instrument calibration, a blackbody was operated inside the ICI3. During standard operation, every 5 minutes the camera would be rotated down from the sky position to view the blackbody, collect an image of the blackbody, perform a flat field correction (FFC), and then collect another image of the blackbody. The temperature of the blackbody was varied every 4 hours in steps of 10 °C between 10 °C and 60 °C. During proper operation, the blackbody was set to 60°C as the ICI started, with the next set point going to 10°C and then increasing back up to 60 °C in steps of 10 °C every 4 hours. However, a programming error prevented correct operation at the beginning of the deployment and the blackbody temperature minimum was limited to 30 °C. This error was remedied on 27 November 2012.

After 24+ hours of operation, the series of blackbody images were calibrated with the standard radiometric calibration process. A flowchart of this process is shown in Figure 4-6. The errors between the camera-measured blackbody radiance and the actual blackbody radiance were used to derive a supplemental gain, g_{bb} , and bias correction b_{bb} for the data. These biases were then applied to the output of the standard calibration to produce an improved sky radiance image. This blackbody-adjusted calibration process resulted in equation 4-26.

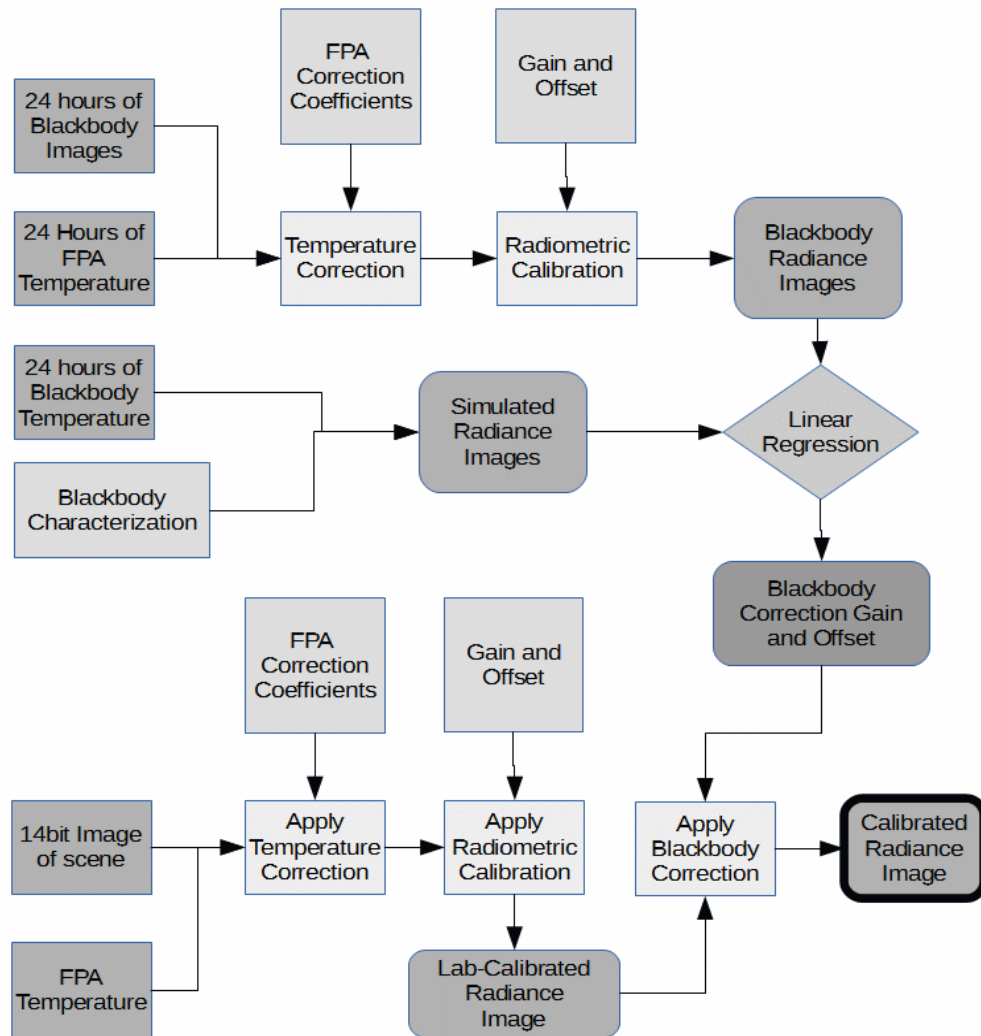


Figure 4-6. Flow chart of the blackbody-adjusted calibration method that incorporated the blackbody calibration source onboard the ICI3 using 24 hours of blackbody images.

$$L_{sky} = g \left[\frac{D_N - b_1 \Delta T - b_s \Delta T^2 - b_s \Delta T^3 + o_1}{1 + m_1 \Delta T} \right] g_{bb} + b g_{bb} + b_{bb}. \quad 4 - 26$$

Deriving the Radiometric Calibration

In the laboratory we derived the coefficients of the FPA-temperature correction and the radiometric calibration by placing the camera in an environmental chamber while viewing a blackbody source. The ambient environment around the camera was then

varied to drive the camera's FPA-temperature. The data collection and subsequent data processing followed the best-practice procedures developed by NWB Sensors, Inc. of Bozeman MT (Nugent, Staal, et al. 2014b; Nugent, Staal, et al. 2014a). These collection procedures included the collection of two data sets to enable the most accurate calibration. The first was a ramp data set, where the FPA temperature was cycled using the environmental chamber. The second was a data set where the camera temperature was held constant while the blackbody was slowly changed over time. These data with non-changing FPA-temperature will be referred to as the soak data set. This second data set was required to ensure accurate measurements of the camera's radiometric calibration.

Two unique sets of soak data were used to derive the radiometric gain and bias for the ICI3. These two gain data sets were collected using slightly different methods. The gain data collected inside the environmental chamber prior to deployment will be referred to as the 2012 gain calibration. After the deployment a second calibration set was collected outside the environmental chamber and will be referred to as the 2016 gain calibration. This resulted in two unique calibrations for the ICI3 systems. The first used the FPA-temperature data derived before the instrument was sent to NSA, along with a soak data set derived at the same time. The second used the same FPA calibration data set, but the soak data set was derived after the instrument was returned to MSU.

The following figures show the data from the 2012 calibration test before the instrument was sent to the ARM NSA site. Figure 4-7 shows the blackbody and camera FPA-temperature profiles during the data collection. Figure 4-8 shows the array-averaged digital values measured without FPA-temperature-dependent stabilization.

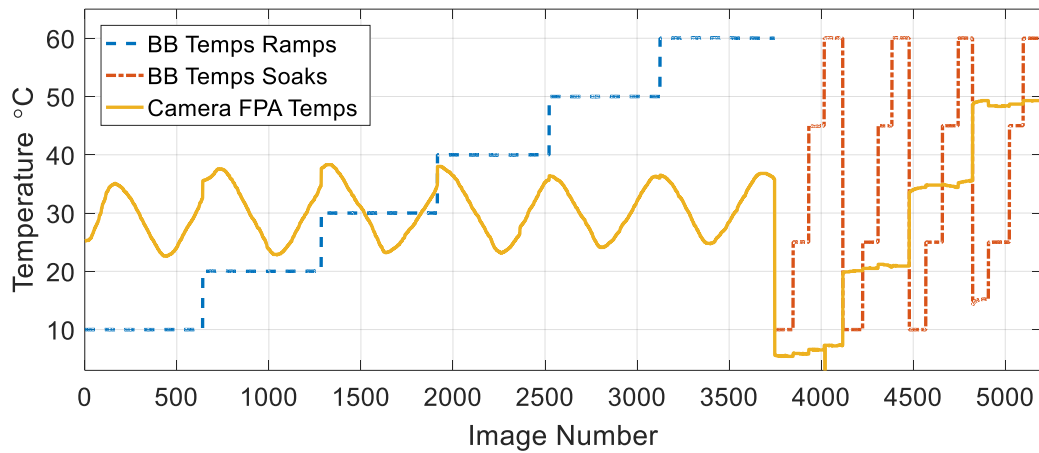


Figure 4-7. Blackbody and camera FPA temperature for the 2012 calibration data.

As per the NWB Sensors Inc. guidelines, during processing the collected data were split into three sets (Nugent, Staal, et al. 2014a). The first was the FPA-temperature dependence calibration set, a collection of both the ramp data and the soak data. The second was the radiometric calibration data set, only comprised of the soak (non-changing FPA-temperature) data. The final is a test data set that is a mix of both the soak and ramp data randomly separated from the previous two data sets.

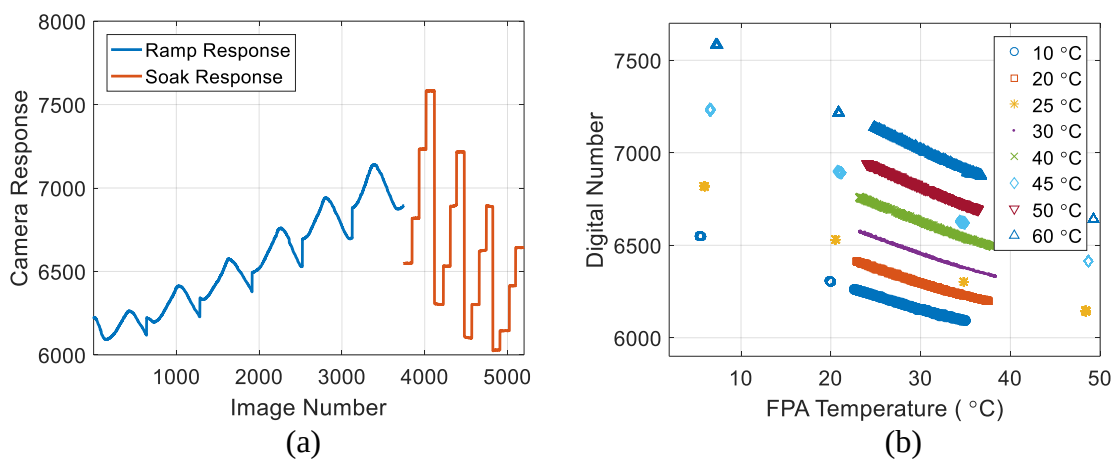


Figure 4-8. Plot of the average digital value without FPA-temperature-dependent stabilization with time (a) and with FPA-Temperature (b). These data are from the 2012 calibration data set.

Figure 4-9 shows the result of the FPA-temperature correction and radiometric calibration applied to the test data. The blackbody set-point temperature is shown in blue, camera measured blackbody temperature using the FPA-temperature correction in red, and camera measured blackbody temperature without compensating for FPA temperature in yellow. The improvement in the data accuracy with the FPA temperature is quite clear. This improvement is further demonstrated by a histogram of the calibration errors for both the FPA-temperature-corrected data and the uncorrected data in Figure 4-10. It is important to note that in this figure the x-axis is over a much smaller range for the corrected data.

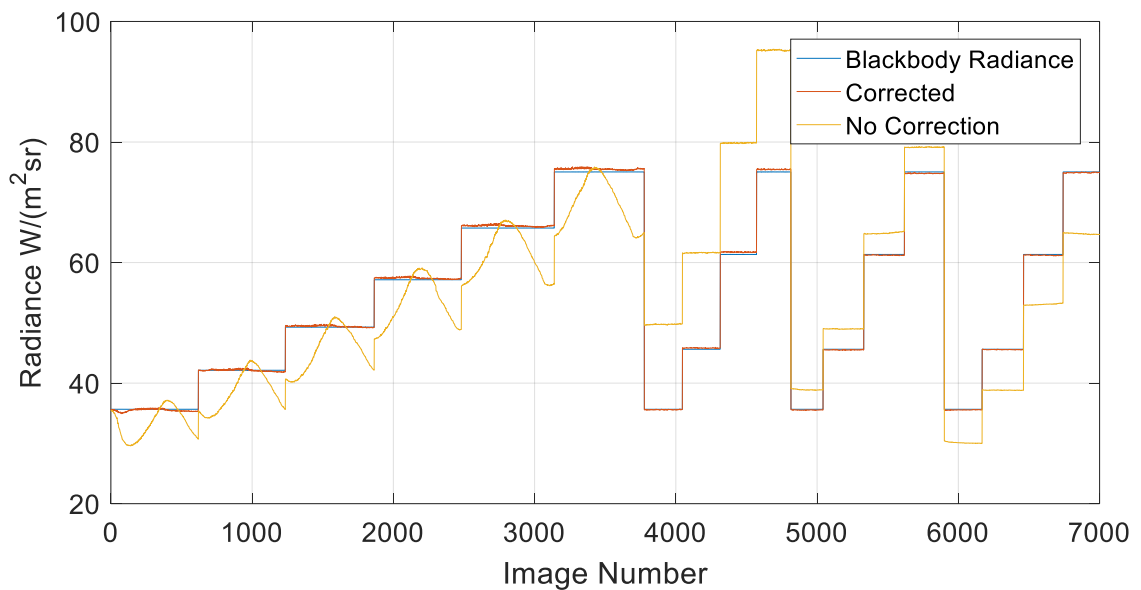


Figure 4-9. Plot of the calibration results showing the blackbody temperature (blue), derived blackbody temperature using the FPA-temperature dependent calibration (red), and derived temperature without compensating for FPA temperature (yellow).

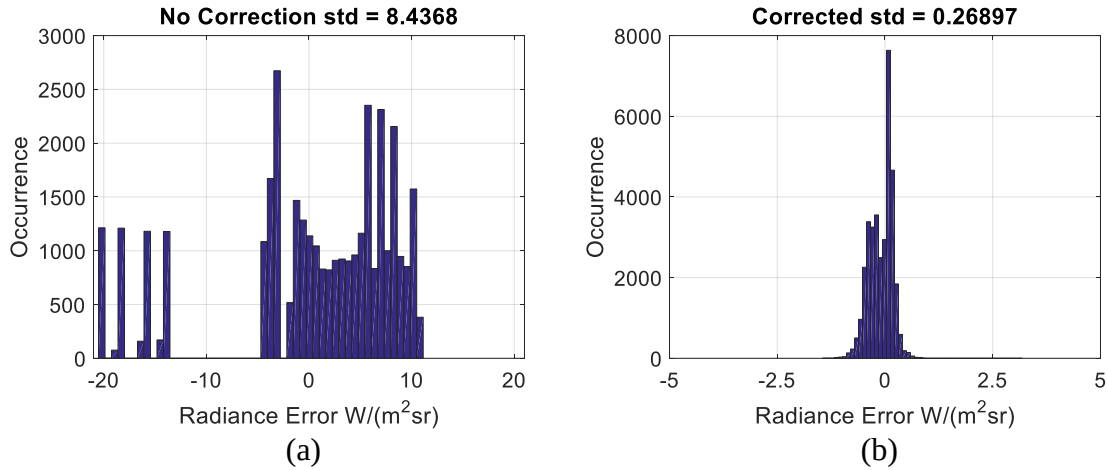


Figure 4-10. Histogram of the resulting derived blackbody radiance errors without FPA-temperature-dependent stabilization (a) and with FPA-temperature dependent stabilization (b). Note the x axis is over a much smaller range for the corrected data.

The resulting calibration gave good results, but no calibration can give perfect results, so there is a need to estimate the uncertainties in the calibrated data. This is of particular importance in the ICI systems. These uncertainties are required when comparing ICI results with other instruments and for understanding the cloud detection limit of the ICI. Table 4-1 summarizes the uncertainties estimated from the ICI calibration data sets.

Table 4-1. Summary of the calibration accuracy

Calibration	σ_t (time)	σ_s (spatial)	Combined σ_r	Calibration Bias L_b
Uncorrected	8.44 W/(m ² sr)	0.071 W/(m ² sr)	8.44 W/(m ² sr)	0.23 W/(m ² sr)
FPA-Temp Corrected	0.27 W/(m ² sr)	0.067 W/(m ² sr)	0.28 W/(m ² sr)	-0.09 W/(m ² sr)

In the ICI radiometric calibration there are two main types of uncertainty: variation of a pixel in time σ_t , and pixel-to-pixel variations across the focal plane array σ_s . The combined radiometric standard deviation σ_r is the estimate of the total radiometric

uncertainty with the assumption that σ_t and σ_s are independent. The calibration bias is the deviation from zero mean error, and was found to be quite small for this camera.

Spectral Response Calibration

To enable radiometric calibration of the ICI3, the spectral responsivity of the camera and lens system had to be understood. MSU did not have the equipment to directly measure the spectral responsivity of the camera, but it did have methods of measuring the transmission of the ICI3 optics. The same model lens, IEM wide FOV LWIR lens, had been measured with an FTIR spectrometer on a previous project. In those measurements, the transmission of the lens was determined by viewing a blackbody target with and without the lens in the system. The response of the camera was estimated based on data provided by FLIR Systems, Inc. for a variety of Photon cameras. The combination of the Photon response and the lens transmission allowed for an estimate of the ICI3 spectral responsivity to be determined, which was used during the deployment to the ARM NSA site. These data are shown in Figure 4-11.

After the deployment of the ICI3 at the ARM NSA site it was discovered this spectral response was not accurate enough to provide good comparisons between the ICI3 and the AERI spectro-radiometer deployed at the site. Therefore, two approaches were attempted to derive the ICI3 spectral response based on the AERI data.

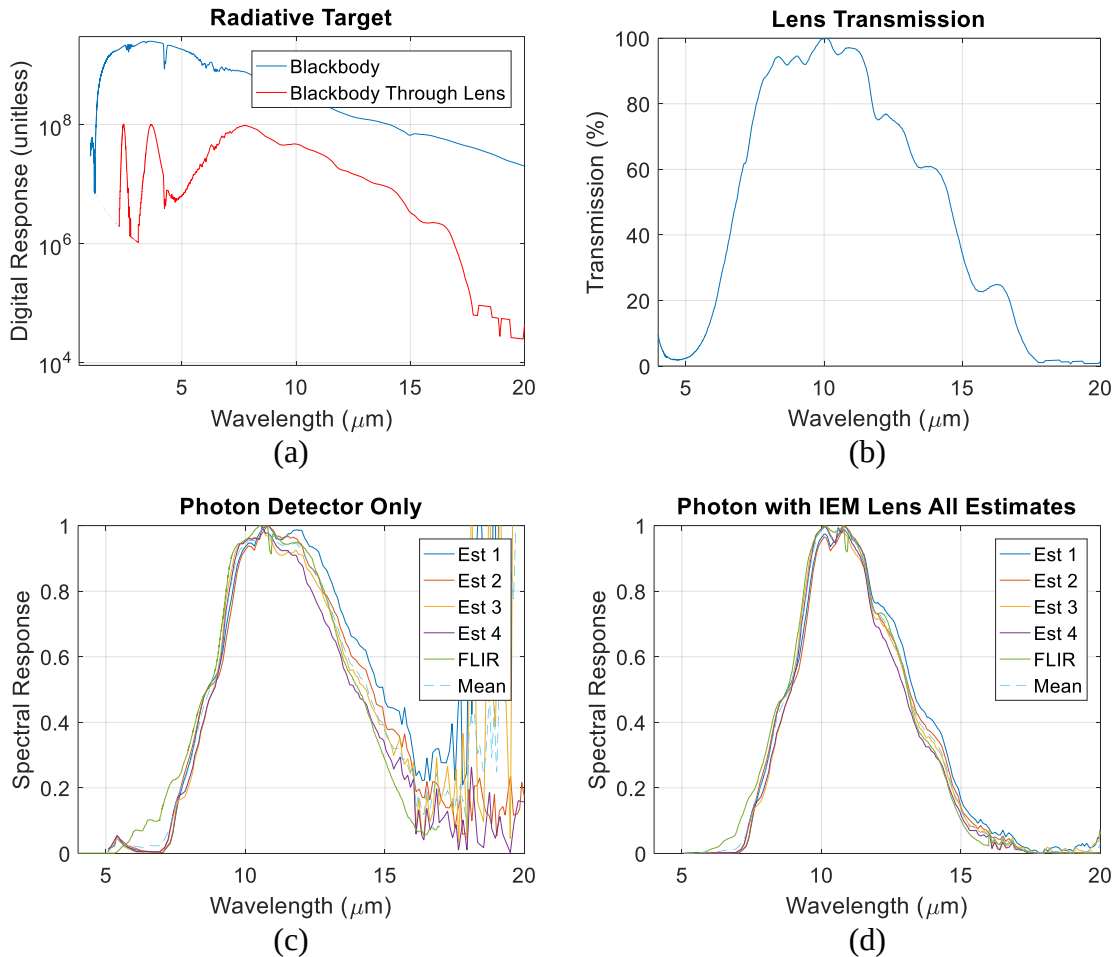


Figure 4-11. The derivation of the best estimates of the ICI3 responsivity: (a) the response of the FTIR directly viewing blackbody target (blue) and through the ICI lens (red); (b) normalized transmission of the lens; (c) Photon detector and filter (no lens) response best estimates; and (d) total spectral response of the FLIR Photon with the IEM lens.

Derivation of the Spectral Response The first was a direct derivation by

attempting to solve the calibration equations and AERI integrals over a large number of measurements. This method was shown to be mathematically possible and worked with simulated data, and worked with AERI data and a simulated camera, but did not work with ICI3 and AERI data. This is likely due to errors present in the ICI3 data.

Experiments showed that even a small amount of noise in the simulated camera caused large variations in the derived bandwidth.

Genetic Algorithms The second approach was a genetic algorithm, which was successful in using the AERI data to infer an ICI3 bandwidth. This algorithm used the laboratory estimates of the ICI3 bandwidth as a starting reference. With each generation small random changes were made at 0.5 μm intervals. Then each bandwidth was evaluated based on the requirement that AERI data integrated across the new spectral responsivity and the ICI3 sky data calibrated with the spectral responsivity should have a 1:1 relationship. This algorithm produced a large number of bandwidth estimates that came close to this relationship, the mean of which was used as the best estimate of the ICI3 response. The mean of these bandwidths and their spectral standard deviation are shown in Figure 4-12, with the genetic-algorithm-derived spectral response shown in red and the FTIR-estimated response in blue.

The genetic-algorithm-derived response deviated from the FTIR-estimated response at wavelengths shorter than 10 μm . Both showed significant response outside of the atmospheric window and had similar uncertainties. The genetic-algorithm-derived spectral response had a higher response in the 6 μm to 10 μm region. This response outside the atmospheric window was consistent with industry data for bare microbolometers, which have been shown to have spectral responsivity from 2 μm to 40 μm and longer (Rogalski 2003).

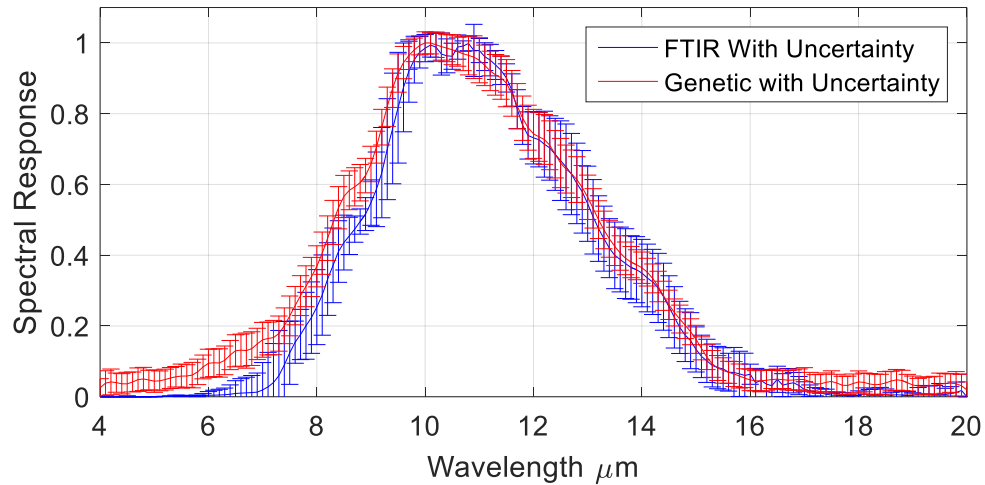


Figure 4-12. Genetic-algorithm-derived spectral response (red) with the mean FTIR-estimated ICI response (blue). The genetic-algorithm-derived response deviated from the FTIR-estimated response at wavelengths shorter than 10 μm . Both show significant response outside of the atmospheric window and had similar uncertainties.

Detector Noise

Separate from the radiometric uncertainty in the ICI3 systems was the true sensor noise. This noise leads to the minimum difference in scene radiance (or temperature) that the imager can perceive. Understanding this noise in the ICI3 is required to understand the thermal resolution of the sensor and the limit of sensor performance (Jovanovi et al. 2014). In a cloud imager this leads to the minimum detectable cloud. This minimum cloud is the cloud that provides an increase in radiance (or temperature) above the clear sky that is sufficiently greater than the noise to allow detection.

Noise Equivalent Temperature Difference

Noise equivalent temperature difference (NETD), also known as noise equivalent differential temperature (NEDT), is a parameter typically used to specify the noise

sensitivity of LWIR cameras. NETD is defined as the temperature difference that produces a signal equal to the camera's temporal noise, and can be described by (Dereniak & Boreman 1996)

$$NETD = \frac{4(F\#)^2 \sqrt{\Delta f}}{\pi D^* (\partial L / \partial T) \sqrt{A_d}}. \quad 4 - 27$$

This equation includes camera parameters such as $F\#$, the f-number of the camera; A_d , the area of the detector; Δf , the electrical bandwidth; D^* , the specific detectivity of the detector; and $\partial L / \partial T$, the change of radiance L for a change of scene brightness temperature T for the specific bandwidth of the detector. Most of these parameters were unknown for the camera in the ICI3, as in most cameras. Thus NETD was determined by viewing a constant blackbody source and dividing the standard deviation of the signal (noise) by the camera's response per degree (at that scene temperature).

$$NETD = \frac{\sigma_{rms}}{\Delta S / \Delta T}. \quad 4 - 28$$

The NETD for a typical Photon camera was reported as 38 mK normalized to F/1 (Kostrzewa et al. 2005). It is common practice for these parameters to be specified for an F/1 system; however, the ICI3 used a F/1.4 lens. To scale the NETD from F/1 to F/1.4, first note that the NETD is proportional to $F\#^2$. Thus the NETD for a specific $F\#$ can be found from

$$NETD_{F\#} = NETD_{F1} (F\#)^2. \quad 4 - 29$$

For the FLIR Photon this gives an $F\#$ -corrected NETD of 74 mK.

The NETD metric is complicated by the nonlinear relationship between radiance and temperature over any detector bandwidth, as shown by the Planck equation. Thus it

will change with scene temperature. This limits the effectiveness of NETD as a metric in LWIR cloud imagers.

Noise Equivalent Radiance In LWIR cloud imagers the noise- equivalent radiance (NER) should be used rather than NETD. This parameter is similar to NETD, but it describes the minimum resolvable radiance difference. This can be more accurate, as the cameras response to radiance is linear over a large range of input scenes (Rogers et al. 2014).

NER was measured in a similar manner as NETD. The camera viewed a constant blackbody source at one or more radiance levels and the NER was calculated as the standard deviation of the signal divided by the radiance responsivity:

$$NER = \frac{\sigma_{rms}}{\Delta S / \Delta L}. \quad 4 - 30$$

Measurements of NER and NETD

To measure the NER in the ICI3, the camera was placed in an environmental chamber with a blackbody source filling the entire field of view. The camera was soaked at temperatures from 0 °C to 40 °C in steps of 10 °C to vary the FPA temperature. During each soak the scene temperature was varied from 10 °C to 60 °C in 10 °C steps, with each step having a 1-hour stabilization time before each data collection period. During the collection period, 256 frames were collected every few seconds. From these frames the standard deviation from each pixel could be determined. Measurement of noise only requires a single scene, but for these measurements the FPA temperature and the scene temperature were varied to observe any dependence on these parameters in the derived

NER. The NETD also was derived to allow for comparison with the manufacturer specifications.

There is a difference between the temporal noise in a detector and the fixed pattern noise that exists across any detector array. Care needs to be taken to separate the temporal noise from the fixed pattern noise (Chao & Huang 1998; Jovanovi et al. 2014). The flat field correction or non-uniformity correction of the camera is intended to reduce the fix-pattern noise (Mudau et al. 2011) and has been shown to have an impact on the noise present in the sensor (Chao & Huang 1998). Therefore, in the ICI3 noise measurement it was determined to measure the noise under normal operating conditions, using the camera FFC (NUC), and operating under the assumption that any post-FFC residual fixed pattern noise contributed to the overall system noise.

Results of the ICI3 Noise Measurements The NER and NETD measured for the ICI3 camera are shown in Figure 4-13. These histograms represent the full-frame-derived noise. Both spatial and temporal averaging can improve the noise performance. During normal operation of the ICI3 a 15 frame temporal average was used for each sky image, but no spatial averaging was applied to the images. Because of this, a similar averaging was applied to the second set of histograms. The reduction of the noise with this averaging was significant, but slightly less than the ideal $1/\sqrt{N}$ theoretical reduction.

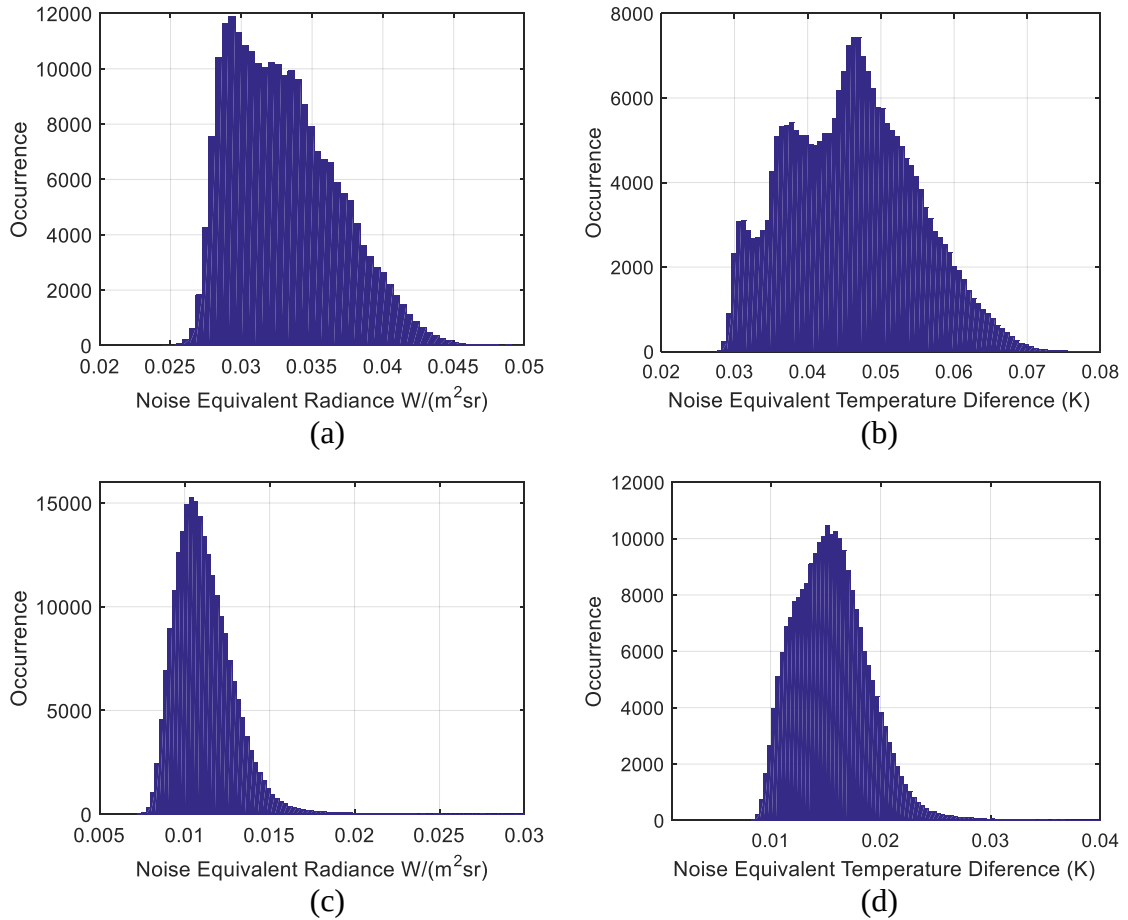


Figure 4-13. Histogram of the full frame derived NER (a) and NETD (b) and the NER and NETD with a 15-frame average (c) and (d), as in the standard operating mode of the ICI3 during the ARM NSA deployment.

The radiometric projection of the aperture and detector areas and vignetting by internal lens elements causes an angle-dependent fall-off in imaging systems, where the power received from the scene decreases with increased angle from the optical axis. In a simple lens this fall-off follows a $\cos^4$ dependence with angle. Care must be taken to account for the fall-off that occurs in the images if attempting to measure the response for the bare detector (Rogers et al. 2014). In the case of the ICI, this power fall-off causes a real increase in NER near the edges of the FOV. Figure 4-14 shows the spatial variation

of the NER across the FPA of the ICI3. This variation is due to a constant noise power across the FPA but a decrease in radiometric power from the scene near the edges of the field of view. This variation must be considered when estimating the cloud detection capabilities of the ICI3.

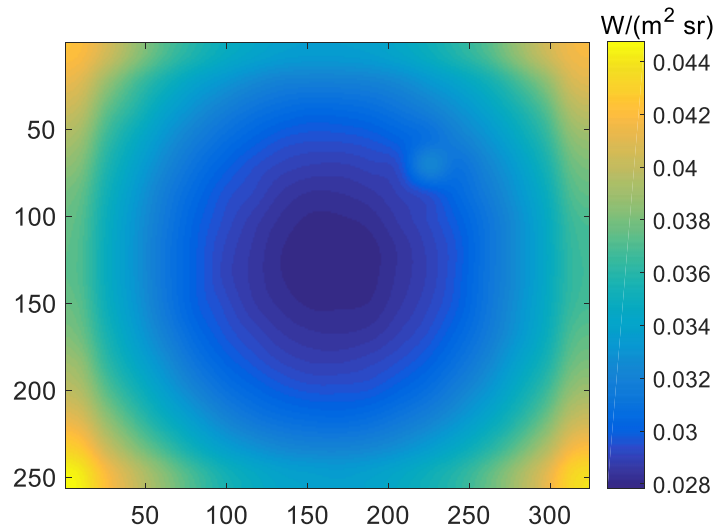


Figure 4-14. Variation of the NER across the imager's FPA. This is due to a constant noise power across the FPA but a decrease in radiance from the scene near the edges due in part to the $\cos^4$ roll off that occurs near the edge of the field of view.

Flooded-aperture measurements were used to make these measurements, which have been shown to produce overly optimistic estimates of the NETD (Rogers et al. 2014). It is expected this would be similar for NER. For the F/1.4 refractive system in the ICI3, it was estimated that if these effects were present there would be between a 15% and 30% underestimation of the NETD (Rogers et al. 2014) and it can be assumed this similar underestimation would occur with NER. Therefore, when NER measurements were used in the ICI3, both a best case (as measured) and worse case (30% underestimate) were used. Table 4-2 shows the full-frame mean NER and NETD with

and without corrections for these underestimates. NETD measurements fell within the range estimated by the FLIR performance specifications. This was true even when incorporating a 30% underestimation in the measured values. Therefore, it was possible that there is such an underestimation in the measured NETD and NER data. To compensate for this potential error, the 30% corrected uncertainty data have been used as the noise equivalent radiance σ_{NER} .

Table 4-2. Measurement of NER and NETD in the ICI3

Parameter	Single Frame	15 Frame Average
FLIR NETD	< 74 mK	< 18 mK
Measured NETD	46.1 mK	15.7 mK
15% underestimate	54.2 mK	18.5 mK
30% underestimate	65.9 mK	22.4 mK
Measured NER	33.1 mW/(m ² sr)	11.3 mW/(m ² sr)
15% underestimate	38.6 mW/(m ² sr)	13.3 mW/(m ² sr)
30% underestimate	47.3 mW/(m ² sr)	16.1 mW/(m ² sr)

Geometric Camera Calibration and FOV Mapping

The final calibration process to enable the ICI3 cloud imagers was measurement of the instrument field of view. This measurement was required for accurate simulation of clear sky radiance (described in Chapter 5) and accurate measurement of cloud cover statistics. During the ARM NSA deployment, an estimated field of view was used. After the ARM NSA deployment, the field of view for the ICI3 camera and lens was measured using an industry-standard measurement technique.

The process used to measure the field of view used a planar target with a known pattern, imaged from arbitrary angles and distances to determine the distortion of the camera relative to an ideal pinhole or orthoscopic camera. This technique was based on a

two-stage calibration process. First based only on knowledge of the size of the squares in the planar target the images were used to determine the camera's position and orientation relative to the target. Then an intrinsic camera model was determined, which includes focal length, principal point, distortions and other imaging parameters (Tsai 1987; Zhang 2000; Sturm & Maybank 1999). A rapid and semi-automated version of this process was implemented in Matlab using a series of images of a flat black-and-white checkerboard or chessboard target (Lee et al. 2009; Bouguet 2015). This procedure output parameters of focal length, lens displacement, radial distortion, and tangential distortion. This routine was extended to determine the angular size, pointing, and rotation of each pixel.

To perform this process, a checkerboard pattern needed to be constructed that had sufficient contrast in the LWIR. Such patterns have been created by using masked patterns placed in front of a blackbody or similar LWIR source (Vidas et al. 2012), by differentially heating a checkerboard target where the black squares absorb more energy and thus have higher temperature and LWIR radiation (Yahyanejad et al. 2011; Engström et al. 2013), or by using a checkerboard target where the squares have a different emissivity (Engström et al. 2013). The method selected for use in the ICI systems built on the process developed at NWB Sensors, where a black and white target was printed onto a rigid target and placed outside in direct sunlight to differentially heat the black and white squares to produce a thermal checkerboard (Nugent, Staal, et al. 2014c), as illustrated in Figure 4-15.

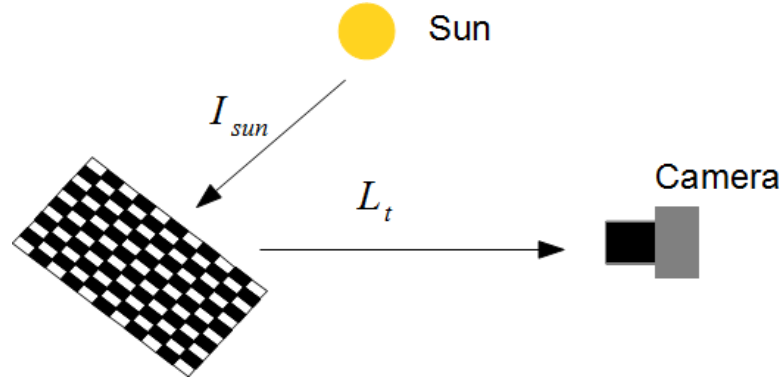


Figure 4-15. Using the Sun as a heating source for the checkerboard pattern. Black squares heat up more, producing a checkerboard pattern in the LWIR. For the calibration presented here, halogen and heat lamps were used rather than the sun.

To implement this indoors, high-intensity, broad-spectrum halogen lamps and heat lamps were used to heat the target. The lamps were aligned to reduce spatial non-uniformity in the heated surface, but some non-uniformity persisted. To create a maximum standard contrast between the hot and cold squares, the images were scaled from 14 to 8 bits using a regionally dependent gray level conversion. Figure 4-16 shows a sub-set of the images collected during the FOV calibration process. In these images the effect of distortion can be observed where the squares appear as squares of uniform size near the center of the image, but are distorted near the edges and appear smaller. Processing of these images followed the procedure developed at NWB Sensors, Inc., including the parameter optimization procedures (Nugent, Staal, et al. 2014c).

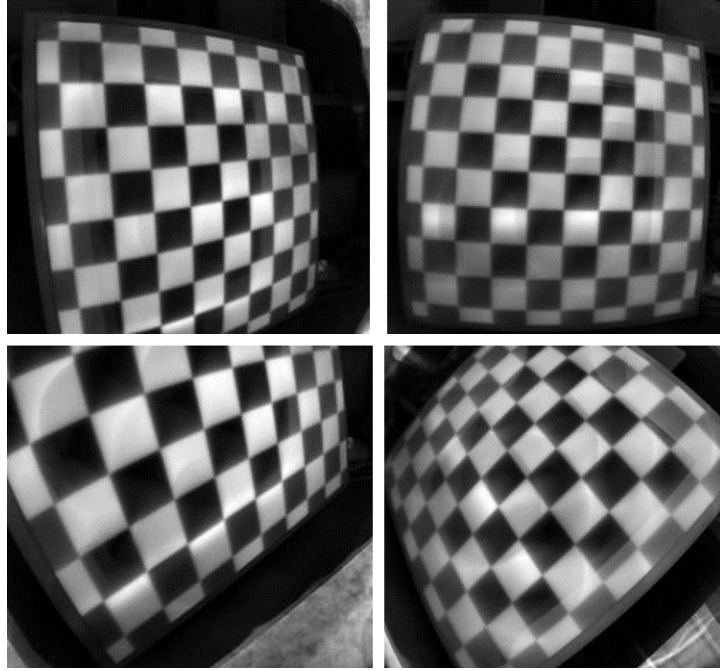


Figure 4-16. Sub-set of images used to solve a series of equations to calculate the lens parameters. Regionally dependent gray level conversion from 14 to 8 bits was performed to maximize contrast for data processing.

After the standard processing, the additional calibration steps were required to derive a zenith angle and azimuth angle array based on the criteria that the optical axis of the camera was pointed at the zenith and the bottom of the camera was pointed north. The parameters were determined by working backward from the derived intrinsic camera parameters that describe imaging for a normalized ideal (pinhole) camera (Bouguet 2015),

$$\mathbf{p}_n = \begin{bmatrix} X_c/Z_c \\ Y_c/Z_c \end{bmatrix} = \begin{bmatrix} x \\ y \end{bmatrix}, \quad 4 - 31$$

where a point $\mathbf{P}$ in object space is described by the vector $\mathbf{XX}_c = [X_c; Y_c; Z_c]$ and $\mathbf{p}_n$ represents the normalized pixel projection from the normalized spatial coordinates $[x, y]$ in both image space and in object space (ideal or pinhole camera). By letting $r^2 = x^2 + y^2$,

image projection of the real camera was described by adding the intrinsic camera parameters of focal length x, y , vector $\mathbf{f}_c$, the principal points vector $\mathbf{c}_c$, the distortions vector $\mathbf{k}_c$, and the skew coefficient vector $\mathbf{a}_c$. The convention that pixel [0,0] is the upper left pixel in the image (as displayed to the user) was used throughout this calibration process. Using these parameters the normalized coordinate $\mathbf{p}_d$ and final pixel vector $\mathbf{p}_p = [x_p, y_p]$ were described by

$$\mathbf{p}_d = (1 + \mathbf{k}_c(1)r^2 + \mathbf{k}_c(2)r^4 + \mathbf{k}_c(5)r^6)\mathbf{x}_n + \begin{bmatrix} 2\mathbf{k}_c(3)xy + \mathbf{k}_c(4)(r^2 + 2x^2) \\ \mathbf{k}_c(3)(r^2 + 2y^2) + 2\mathbf{k}_c(4)xy \end{bmatrix} \quad 4 - 32$$

and:

$$\mathbf{p}_p = \begin{bmatrix} x_p \\ y_p \end{bmatrix} = \begin{bmatrix} \mathbf{f}_c(1)(\mathbf{p}_d(1) + \mathbf{a}_c\mathbf{p}_d(2)) + \mathbf{c}_c(1) \\ \mathbf{f}_c(2)\mathbf{p}_d(2) + \mathbf{c}_c(2) \end{bmatrix}. \quad 4 - 33$$

To determine where each pixel of the ICI array was mapped into the image, the inverse map $\mathbf{p}_p[i,j]$ of pixel locations in image space to the resulting vector in $\mathbf{P}$ in object space was required. There exists no generic algebraic expression for this inverse mapping; however, a numerical solution was been implemented in the Matlab Camera Calibration Toolbox (Bouguet 2015). This solution calculated the normalized pixel vector $\mathbf{p}_n$ in object space. Once this value had been determined in object space, the zenith and azimuth pointing angles for each pixel were determined as the angles of this vector in relation to the optical axis defined by $\mathbf{c}_c$.

Table 4-3 and Table 4-4 summarize the model for the ICI3 camera, including the focal length measured in pixels, and Table 4-4 describes the distortion coefficients. These parameters were used to determine the angular field of view for the ICI3. These angles for each pixel are shown in Figure 4-17 (zenith angle a and azimuth angle b). The

assumption was made that the optical axis of the camera was pointed at the zenith and the bottom of the camera was pointed north. In the zenith angle image the black lines represent a step of 5 degrees.

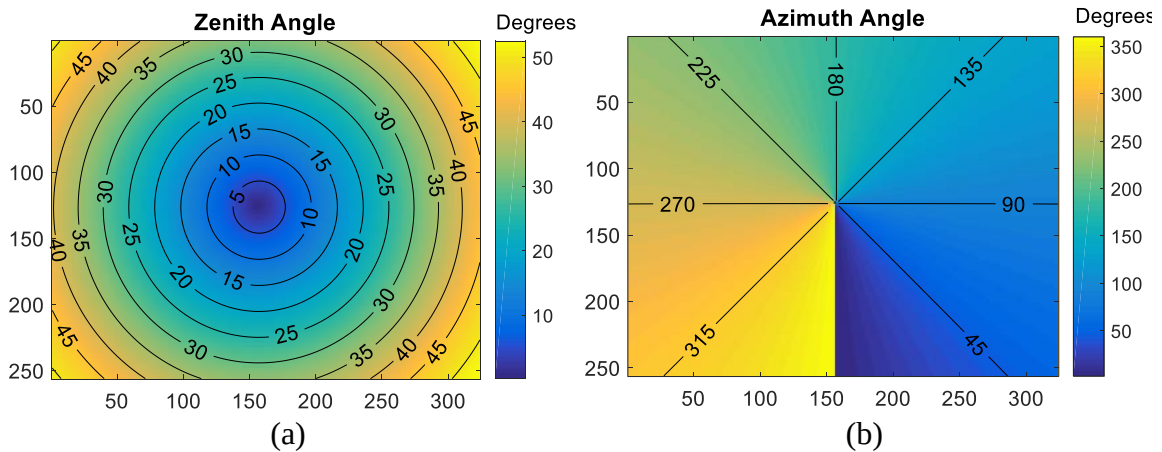


Figure 4-17. The field of view map for the ICI3 camera: (a) the zenith angle; and (b) the azimuth angle, assuming that the optical axis of the camera was pointed at the zenith and the bottom of the camera was pointed north.

From these concentric circles and nearly uniform spacing across the image, it can be seen that the distortion of the lens was low, with only a slight compression of angles at the edges of the image. It is also important to note the optical axis (zero zenith angle) was not at the center of the image, which can lead to errors if not compensated for in the data processing.

Table 4-3. Camera model parameters and uncertainties

Parameter	Value X	Value Y	Uncertainty $\pm 3\sigma$	Uncertainty $\pm 3\sigma$	Units
Focal Length f_c	225.93	226.01	0.95	0.91	Pixels
Principal Point, c_c	157.28	126.30	1.048	0.95	Pixels
Skew α_c	0.00	0.00			Degrees

Table 4-4. Camera distortion model coefficients

Distortion Coefficients					
k_c	-0.33	0.099	0.0017	-0.0021	0.00000
Uncertainty $\pm$	0.0038	0.0037	0.00050	0.00054	0.00000

The re-projection error stated in Table 4-5 provided an estimate of the accuracy of these measurements in units of pixels. This re-projection error was combined with the per-pixel change in FOV to determine the pixel pointing uncertainty shown in Figure 4-18. When applying this to determine the accuracy of the ICI3 data, only the zenith angle uncertainty will directly impact the data processing accuracy.

Table 4-5. Re-projection error

Re-projection Error	Value X	Value Y	Radial	Units
Pixel Error $\pm 3\sigma$	0.38437	0.47241	0.6090	Pixels

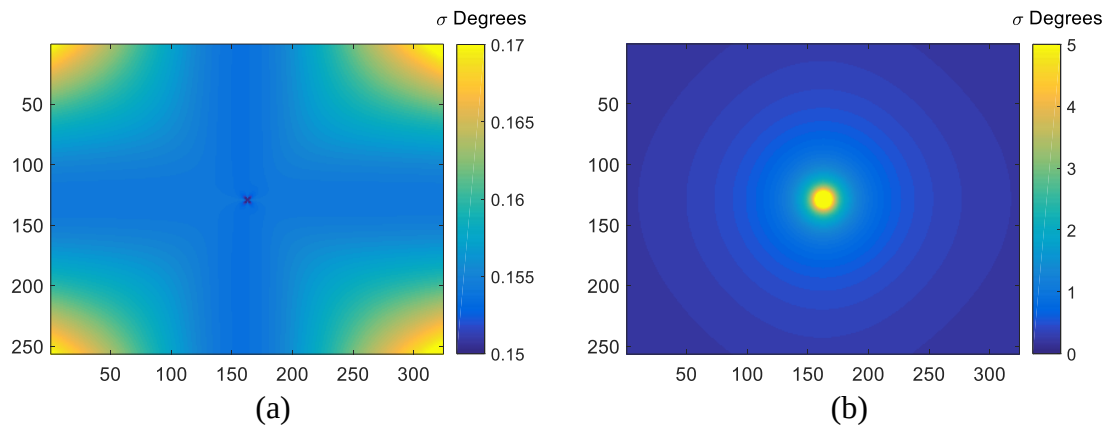


Figure 4-18. Field of view uncertainty maps for the ICI3 camera based on the re-projection 3σ error: (a) uncertainty in the zenith angle; and (b) uncertainty in the azimuth angle.

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DATA PROCESSING AND CLOUD DETECTION ALGORITHMS

ICI3 Data Processing

The cloud detection and classification algorithms form the core of the ICI systems and distinguish these systems from other radiometric LWIR imagers. All algorithms used with the ARM NSA data provide cloud classification, either by removing atmospheric emission from a radiometrically calibrated sky image and then processing the remaining signal to provide cloud detection and classification, or using a data classification tree to directly classifying clouds based on image features. The radiometric processors differed in the processes used to determine the atmospheric emission. Once the cloud emission had been isolated from the clear sky emission, additional processing steps were used to classify the clouds or to extract cloud properties. These additional properties included the statistical descriptions of the cloud data and cloud physical properties such as cloud optical depth, or cloud attenuation.

The standard cloud processing algorithm was a direct radiometric detection method. The thermal emission from the clouds and sky measured with an LWIR camera was calibrated to radiance, a model was used to estimate and remove the atmospheric emission, and the remaining signal was processed to detect and classify clouds (Shaw & Nugent 2013). This algorithm required a careful understanding of the sky emission and instrument performance.

Two additional radiometric algorithms were developed with the goal of improving the cloud data when auxiliary instrument data were not available and reducing

dependence on instrument calibration accuracy. As a result, these algorithms were more advanced processing routines. These algorithms first identified clear sky, then used these clear-sky regions to correct for uncertainties in the camera calibration and modeled atmosphere emission. The first of these advanced algorithms used a multistep clear sky identification tree based on radiometric parameters, comparisons with the modeled atmosphere, and comparison of changes within and between images. The second incorporated a support vector machine (SVM) to first identify regions of clear sky. This algorithm was notable that it only used the uncalibrated sky images and spatial changes within and between images to identify the clear sky regions; thus it was independent of camera calibration or clear-sky emission modeling accuracy.

The fourth and final algorithm discussed in this work was a SVM only cloud detection and classification algorithm. In this algorithm a multi-class classifier tree based on seven unique SVMs was used to both detect clear-sky, cloudy-sky, and classify clouds by thickness levels that loosely relate to optical depth. This algorithm provides this classification without using radiometrically calibrated images and without using an atmospheric emission model. All four of these cloud detection algorithms are discussed in detail in this chapter.

Atmospheric Propagation and Cloud Emission Models

Two of the three ICI processing algorithms require accurate models of the clear sky emission to identify regions of clouds and clear sky. All three of the processing methods require a model of expected sky emission to accurately classify clouds and

extract cloud properties. To develop an empirical model of the clear sky and cloud emission, the emission was studied with the MODTRAN radiative transfer code.

MODTRAN is a band-model radiative transfer code that uses a layered model of the atmosphere to simulate the spectral emission and transmission along any atmospheric path (Berk et al. 1999; Berk et al. 1987). This software can incorporate the emission of multiple types of clouds based on both standard models and user defined parameters (Berk et al. 1999). Previous work conducted at MSU incorporated control of MODTRAN into the MATLAB programming environment, with support of running multiple simultaneous simulations on each core of a processing computer. This allowed for tens of thousands of simulations to be run in a manageable length of time.

Clear Sky Radiance Model

The MODTRAN for MATLAB software was used to build an atmospheric emission model specific to the ARM NSA site. Vertical profiles of atmospheric pressure, temperature, and humidity were available from radiosondes launched every six hours from the automated radiosonde system at the NSA ARM site in Barrow, AK (Holdridge & Kyrourac 2015a). MODTRAN models were run for each radiosonde profile from 1 January 2012 through 31 December 2014, a total of 2201 profiles, which bounded the time the ICI3 was deployed at ARM NSA. These data provided a large variety of air temperatures, water vapor levels, and other atmospheric parameters.

To account for the increased emission with zenith angle, each profile was simulated at zenith angles from 0° to 80° in steps of 2.5° , leading to a total of 72,633 simulations. These data were used to derive a model that related the clear-sky radiance

integrated across the ICI3 camera bandwidth, L_{sky} , to the radiance of a blackbody at the surface air temperature L_s and precipitable water vapor column W_p in cm for each zenith angle. The resulting model is shown in Equation 1. The coefficients of the model A , B , C , and D are derived from a linear regression for each zenith angle. These coefficients are shown in Figure 5-1 for each of the simulated zenith angles.

$$L_{sky} = L_s W_p A + W_p B + L_s C + D \quad 5 - 1$$

It was not feasible to run a unique simulation at each of the 82,944 zenith angles within the ICI3 field of view. Therefore, the clear sky emission was calculated for each of the angles contained in the model, then a spline interpolation was used to create clear sky emission at the zenith angle of each pixel.

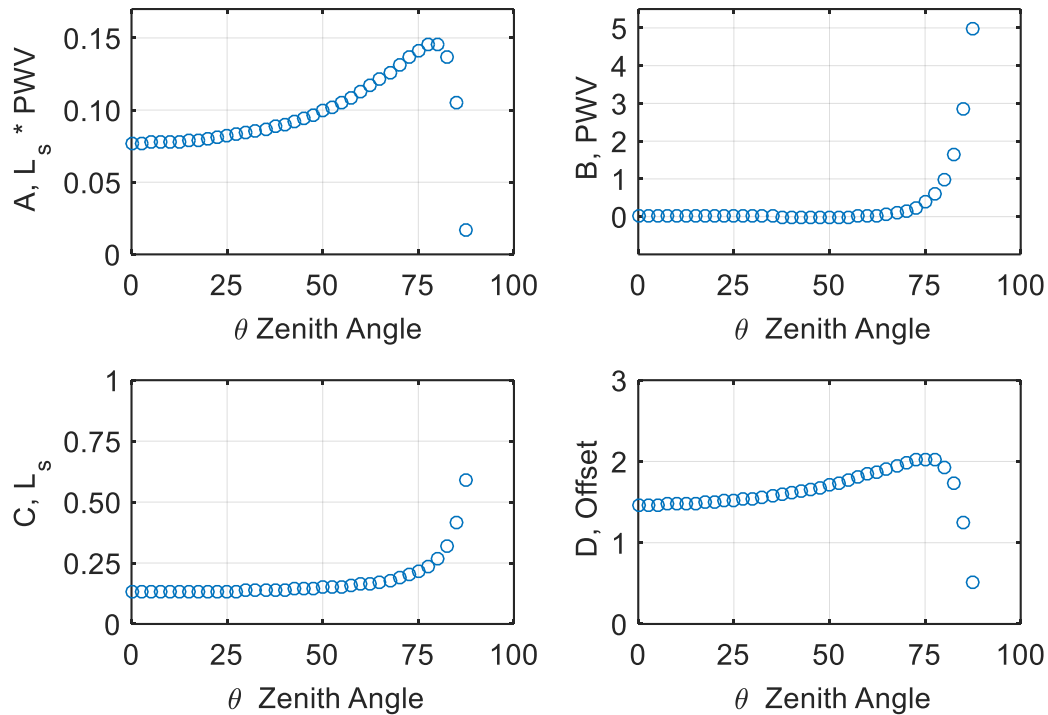


Figure 5-1. The coefficient of the NSA atmosphere radiance model calculated for zenith angles from 0° to 80°.

Sources of the Required Data These models required measurements of the precipitable water vapor and surface air temperature. These data were available from instruments co-located with the ICI3 at the ARM NSA site. Meteorological data, including surface air temperature and dewpoint temperature, were measured by the ARM MET (Holdridge & Kyrouac 2015b). Precipitable water vapor data at NSA were acquired from the NSA microwave radiometer when available (± 5 minutes of a ICI3 image) or otherwise estimated using a Reitan algorithm (Reitan 1963; Tomasi 1981) that estimated the precipitable water vapor from the dewpoint temperature. Accurate use of the Reitan model required the coefficients to be derived for a specific location (Tomasi 1981). The ARM NSA Reitan model parameters were built using dewpoint from the MET station and precipitable water vapor from the microwave radiometer.

This Reitan relationship relates the natural logarithm of the precipitable water vapor to a linear function of the surface dew point,

$$\ln(W_p) = aT_{dew} + b, \quad 5 - 2$$

where T_{dew} is the dew point temperature (in Kelvin) and a and b are coefficients specific to the location of interest.

A Reitan model specific for TMF was derived using W_p data from radiosondes launched at TMF and from the TMF solar radiometer, along with dew point measurements from the TMF weather station. Figure 5-2 shows these data with the Reitan model for each data set. A least-squares fit to these data was used to derive the coefficients a and b , in equation 5-3:

$$\ln(W_p) = 0.056T_{dew} - 15.01. \quad 5 - 3$$

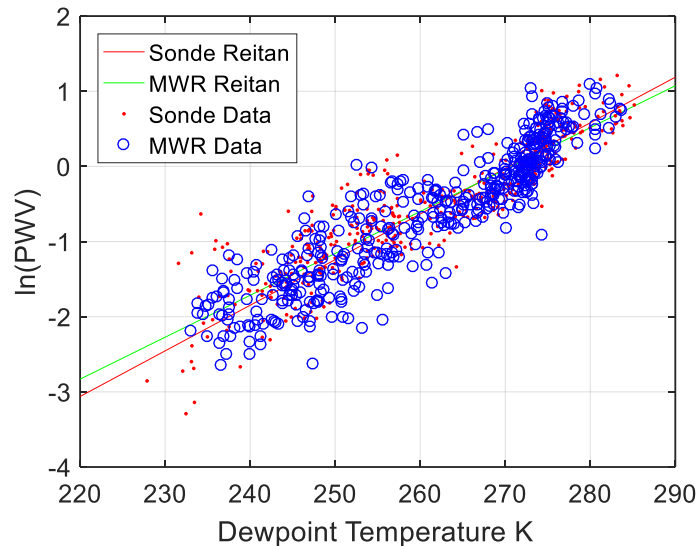


Figure 5-2. Reitan relationship between precipitable water vapor and dewpoint temperature for the ARM NSA site derived from radiosonde data (blue circles and red line) and the microwave radiometer (red dots and green line).

Uncertainty in the Clear Sky Radiance Model There were multiple sources of uncertainty in the modeled clear sky radiance. These included uncertainties in the data sets used as inputs into the model, including surface temperature, dewpoint, and precipitable water vapor. The uncertainty in these sources were highly dependent on the instrument by which they are acquired. Because of this, care was taken to properly account for these uncertainties. Chapter 6 will present a full uncertainty model for the clear sky radiance data.

Cloud Detection and Classification

Clouds were detected in the ICI3 data processing using a multi-level threshold that classified the residual radiance after the removal of the clear sky emission. These

thresholds classified the clouds into different categories used to associate the clouds with optical properties such as optical depth (OD) and attenuation (Nugent et al. 2009).

Cloud classification was enabled by relationships that relate LWIR emission to cloud OD. First, the relationship between cloud OD and cloud emissivity in the LWIR predicts increasing cloud emission for increasing OD of a constant-temperature cloud (Fu & Liou 1993; Lynch et al. 2002). Second, the probability of higher-OD clouds decreases with increasing cloud-base altitude (Lynch et al. 2002). This occurrence probability is highest in the tropopause, where the temperature of the atmosphere is constant with altitude. These combined relationships allow the cloud residual radiance (after removal of atmospheric emission) to be associated to a cloud optical depth with high accuracy. In LWIR imagery these relationships were used to derive cloud OD up to an OD 3. Optically thicker clouds radiate as blackbodies and thus their emission relates more to temperature than to OD.

To develop these thresholds, a large number of simulations were run with the MODTRAN for MATLAB environment. These simulations required both atmospheric profiles and measurements of cloud height, thickness, and optical properties. The atmospheric profiles were provided by the radiosondes launched 4x daily at the ARM NSA site (Holdridge & Kyrouac 2015a; Holdridge et al. 2011). Cloud models used 5113 measurements of cloud base height, cloud physical thickness (cloud top height minus cloud base height), and cloud optical depth measured from the Raman LIDAR at the ARM Sothorn Great Planes (SGP) site located at Lamont, OK (Goldsmith et al. 1997). A

sufficiently large set of cloud height and cloud optical depth was not available from the ARM NSA site, so cloud data from the ARM SGP site were used.

To account for seasonal variability while keeping the number of simulations manageable, radiosonde profiles from each month were averaged to build an ARM NSA atmosphere for each month of the year. Then each of the clouds from the Raman LIDAR were simulated in each of the atmospheres. To account for the increase with zenith angle, each profile was simulated at zenith angles from 0° to 80° in steps of 2.5° . This increase in emission is a result of the increase in physical thickness when observing a cloud at oblique angles. These parameters resulted in a total of 2,024,748 cloud simulations, which were processed to provide a variety of cloud emission thresholds selected to relate cloud residual radiance with a maximum cloud optical depth. The term maximum optical depth is used because a thin warm cloud can have the same radiance as a thick cold cloud.

The Cloud Detection and Optical Depth Thresholds To set the cloud optical depth thresholds, regions were determined where 95% of the clouds had OD attenuation less than a specified value. This technique, therefore, binned clouds by the maximum expected OD or dB attenuation at 95% confidence. For example, in the January model 95% of the clouds with emission less than $4.48 \text{ W}/(\text{m}^2 \text{ sr})$ and greater than $2.83 \text{ W}/(\text{m}^2 \text{ sr})$ had an OD less than 1. All clouds with radiance greater than threshold level 7, $7.23 \text{ W}/(\text{m}^2 \text{ sr})$ for January, were classified as level 8 or thick clouds. The full set of zenith-equivalent optical depth thresholds used for cloud detection in the ICI3 ARM NSA deployment are summarized in Table 5-1 and Table 5-2. The cloud thresholds from level

8 clouds are not shown, these clouds are clouds with a radiance value greater than the radiance threshold for level 7.

Table 5-1. Optical Depth and Attenuation for the ICI2

Threshold Number	Optical Depth	Attenuation (dB)
1	< 0.06	< 0.26
2	< 0.15	< 0.65
3	< 0.25	< 1.09
4	< 0.5	< 2.17
5	< 1	< 4.34
6	< 2	< 8.68
7	< 3	< 13.02
8	> 3	> 13.02

Table 5-2. Calculated Thresholds for the ICI3 at NSA throughout the year in $W/(m^2 \text{ sr})$

Lev	OD	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
1	< 0.06	0.07	0.08	0.07	0.07	0.08	0.07	0.08	0.03	0.08	0.07	0.03	0.02
2	< 0.15	0.95	1.00	0.97	1.02	1.03	0.96	0.99	0.99	1.02	0.93	0.86	0.90
3	< 0.25	1.46	1.52	1.49	1.56	1.57	1.53	1.59	1.60	1.58	1.47	1.41	1.49
4	< 0.5	2.83	2.96	2.93	3.03	3.08	2.83	2.91	2.99	3.05	2.79	2.55	2.71
5	< 1	4.48	4.71	4.60	4.77	4.88	4.64	4.72	4.81	4.82	4.46	4.20	4.47
6	< 2	6.56	6.82	6.71	6.91	7.07	7.57	7.78	7.54	7.22	6.73	6.32	6.63
7	< 3	7.23	8.51	7.36	7.81	8.09	11.21	11.27	10.87	9.93	9.37	9.08	7.41
8	> 3												

Uncertainty in the Cloud Detection Thresholds These cloud optical depth thresholds had an uncertainty based largely on the bandwidth uncertainty in the cameras. To assess this uncertainty, the cloud simulations were integrated and thresholds were derived using each of the bandwidths derived by the genetic algorithm used to determine

the camera response. The radiance standard deviation was determined by comparing all of these cloud thresholds. These uncertainties are presented in Table 5-3. For most of the thresholds the uncertainty is 4.6%, with the largest deviation from this occurring for the lowest cloud OD threshold, which had an uncertainty of 23%.

Table 5-3. Cloud Detection Uncertainty

Threshold Number	Optical Depth	Mean Radiance Level $W/(m^2 \text{ sr})$	Uncertainty $\pm W/(m^2 \text{ sr})$	Uncertainty %
1	< 0.06	0.06	0.01	23%
2	< 0.15	0.97	0.045	4.6%
3	< 0.25	1.52	0.07	4.6%
4	< 0.5	2.89	0.13	4.6%
5	< 1	4.63	0.21	4.6%
6	< 2	6.99	0.32	4.6%
7	< 3	9.01	0.40	4.4%
8	> 3	> 9.02	0.40	4.4%

Direct Cloud Optical Depth Relationship Rather than the threshold-based approach, a continuous relationship was used to determine a finer-resolution cloud OD by determining the most probable cloud OD for a given cloud residual radiance. To determine this relationship, the natural logarithm of the cloud residual radiance, L_{rr} , was fit to the natural logarithm of the cloud OD as a first-order linear relationship. This relationship allowed the cloud OD to be derived directly from the residual radiance once the cloud had been detected using the lowest cloud detection threshold. This relationship is shown in Figure 5-3. The dashed red lines in the figure represent the range of OD values that can be associated with a given residual radiance level.

Uncertainty in this relationship was largely dependent on the camera bandwidth, as in the thresholding method. To derive this uncertainty, the range of camera bandwidths were used to derive the relationship, which led to a one-standard-deviation uncertainty of ± 0.002 for the gain of the linear relationship and ± 0.054 for the offset. These values can be used to understand the OD uncertainty in the OD comparisons conducted in Chapter 7.

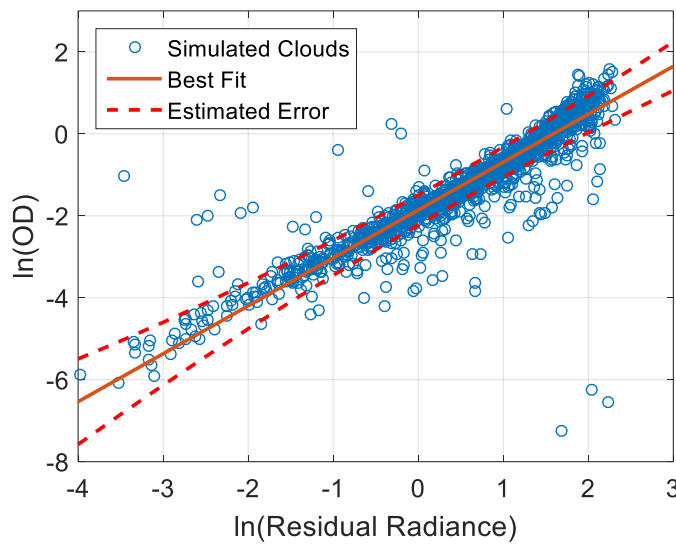


Figure 5-3. Direct optical depth retrieval based on the logarithm of the cloud residual radiance.

Cloud Optical Depth with Cloud Height and Temperature When cloud height information and profiles of the atmosphere were available, another cloud OD method was enabled. First, the cloud emissivity was determined, then cloud OD was determined through the relationship between OD and emissivity. Cloud emissivity was determined using the cloud residual radiance, cloud height, and a radiometric transfer model of the atmosphere.

The residual radiance was used as the emission from the cloud. Temperature from an atmosphere profile and cloud height was used to determine the temperature of the cloud. The blackbody spectral emission at the cloud temperature was determined by the Planck equation. This radiance was then adjusted by a MODTRAN simulation of the atmospheric transmission from the cloud height to the ground. Integrating this transmitted blackbody emission gave the signal the sensor would measure for a blackbody cloud at the cloud height and temperature. The cloud emissivity was determined by dividing the measured cloud emission by the emission of the simulated blackbody-cloud temperature. Once the cloud emissivity was determined, this value was converted to cloud OD, τ , in an equation such as shown in equation 5-4.

$$\tau = \frac{\ln(1 - \varepsilon)}{-0.79} \quad 5 - 4$$

Considerations for Cloud Height and Atmospheric Emission A variety of methods for determining the cloud height have been tried. These included cloud base height, average of cloud base and cloud top, and a weighted average of cloud base and cloud top. The highest correlation was found when the cloud height and corresponding temperature were calculated with a weighted average that used 90% of the base height and 10% of the top height. This method made no assumptions about the cloud location in the atmosphere or the expected distribution of clouds with similar emission, and therefore it could determine cloud OD to values greater than the OD = 3 limit of the other cloud OD method, however uncertainty rapidly increases for clouds with higher OD.

Cloud Detection Algorithms

All of these cloud detection methods required the atmosphere emission to be modeled for determination of the residual radiance of the cloud. The ICI3 utilized three different methods of determining this residual radiance. The following sections described each of these methods.

The Direct Cloud Detection Method

The direct cloud detection method calculated the atmospheric emission using a model derived from MODTRAN simulations. This model required measurements of precipitable water vapor and surface air temperature, along with a per-pixel zenith angle map of the camera. The atmospheric radiance was subtracted from the calibrated sky radiance image. Then a series of thresholds were applied, with the first being a cloud / no cloud level based on the calibration accuracy and uncertainty level in the camera. Any pixel above this threshold was classified as a cloud. Secondary thresholds were used to classify clouds by optical depth. This process is outlined in Figure 5-4, in this figure it is important to note the sky radiance and clear sky images have different scales to show the change with angle observed in the clear sky emission.

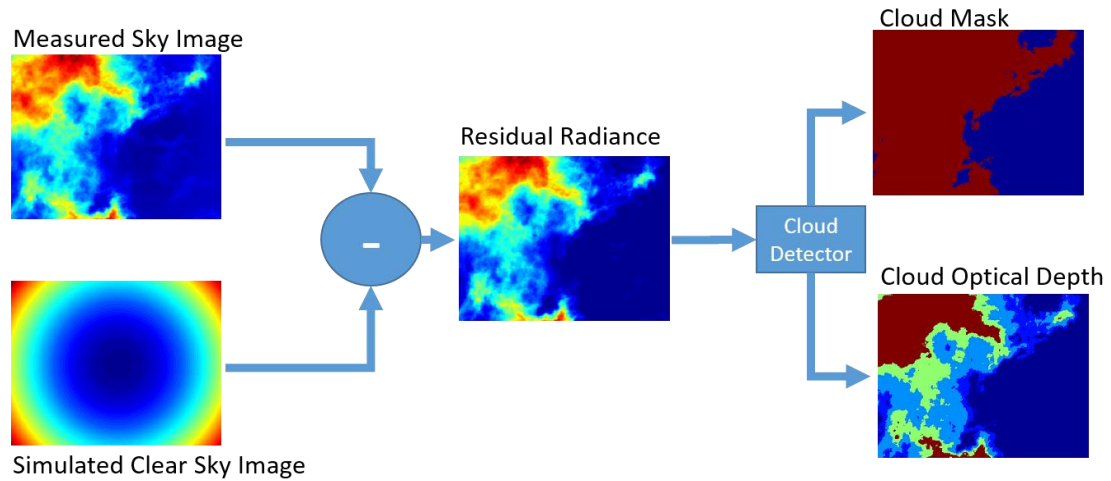


Figure 5-4. The ICI direct cloud detection method. It is important to note the sky radiance and clear sky images have different scales to show the change with angle observed in the clear sky emission.

Adaptive Data Processing

This model makes the assumption that there may be errors present in either the simulated sky radiance or the measured scene radiance. These sources could be errors in precipitable water vapor values, surface temperature measurements, camera bandwidths, or camera calibrations. This leads to a situation where if the direct cloud detection algorithm is used the residual radiance will not be correct. This prevents the cloud thresholds from being applied in an accurate manner.

Correcting the Simulated Sky Radiance and Cloud Detection To correct for the error present in the residual radiance clear sky pixels were detected using a method independent of the cloud detection thresholds. These sky pixels were then entered into a history of detection along with the modeled sky radiance and detected sky radiance for these pixels. If more than 5000 sampled pixels exist, over more than 30% of the zenith angle range, then a clear sky correction was derived. The correction is a first order linear

fit that relates the measured clear sky radiance divided by the airmass to the modeled clear sky radiance, L_{sky} , divided by the airmass, in this equation the offset becomes a function of airmass. This results in a corrected residual radiance image based on the following equation:

$$L_{rr}(x, y) = L_m(x, y) - \frac{L_{sky}(x, y)}{sec(\theta(x, y))} S_{am} - S_{ab} sec(\theta(x, y)). \quad 5 - 5$$

In this equation $L_m(x, y)$ is the radiance measured at each pixel, $L_{sky}(x, y)$ is the radiance modeled for each pixel, $sec(\theta(x, y))$ is the airmass for each pixel, S_{am} is the sky adjustment gain coefficient, and $S_{ab} sec(\theta(x, y))$ is the sky adjustment airmass dependent offset. The updated residual radiance image was then used in the cloud detection and optical depth routines. The correction described equation 5-5 will break down at high zenith angles due to the approximation of the airmass by $sec(\theta(x, y))$. To prevent this problem, future versions of this algorithm should incorporate an airmass estimation which includes the curvature of the Earth and atmospheric refraction similar to Young's airmass equation (Young 1994). A flow diagram of this adaptive data processing method is shown in Figure 5-5.

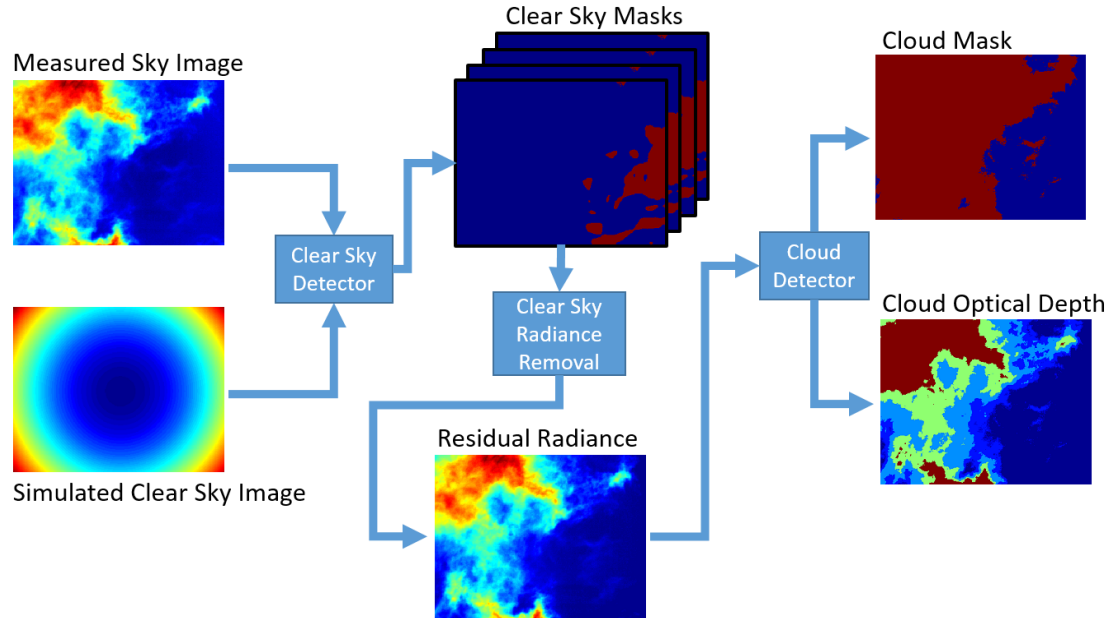


Figure 5-5. The adaptive cloud detection method which assumes errors may exist in the sky radiance or simulated clear sky radiance.

This largest limitation of this algorithm was that it had to be initialized during a time period of clear skies to produce accurate cloud images. This requirement could be reduced by using a guess at the scaling image based on previous data, from days or even weeks in the past. This would allow the imager to produce data with an improved accuracy if started during a period of overcast skies, but data quality would be suspect until sufficiently clear skies were present for a sufficiently long duration. The other limitation was that during long periods of cloudy skies (greater than 4 hours), an estimated sky adjustment had to be used. This estimate was based on the most recent sky adjustment.

Detecting the Clear Sky Without prior knowledge of the source of the error it is difficult to determine if the simulated clear sky radiance or measured radiance is incorrect

based on the scene radiances. However, it is known how a clear sky changes both in time and spatially within an image even if radiance errors exist in the images or the modeled sky. This allows a clear sky detection algorithm to be developed. Once clear skies have been detected these clear sky images can be used to build an adjusted clear sky model that incorporates any radiance biases.

Within the ICI images the clear sky changes in a predictable manner in time over small fields of view, such as the instantaneous field of view (IFOV) of a pixel. The clear sky radiance changes over time scales of hours, where changes due to the clouds takes place over minutes or less. Spatially within the image the clear sky can be described by how it changes with zenith angle and with azimuth angle. Along an almucantar in the image (pixels with the same zenith angle) the clear sky radiance does not change. Along a set of pixels at the same azimuth angle the change of these pixels is predictable based on the airmass method where with increasing path length there is increasing path integrated method. These gradient along zenith angles changes are similar to the same airmass in the modeled sky emission. This airmass scan is similar in concept to similar scans used to produce a Langley plot in the calibration solar monitoring instruments.(Mims III 1992; Mims III 2002). These scans are shown in Figure 5-6, where the blue line represents an almucantar scan and the yellow line represents an airmass or zenith angle scan.

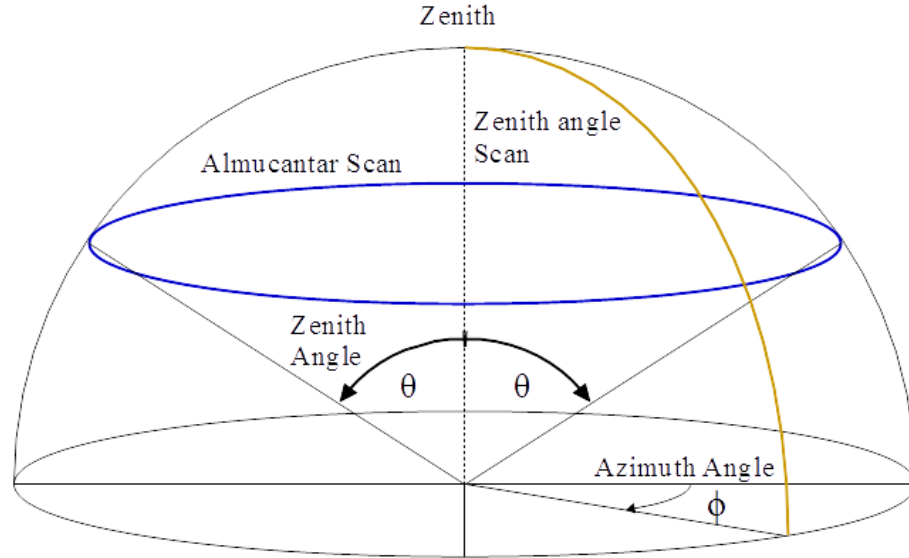


Figure 5-6. Diagram of the Almucantar scan (blue) and zenith angle or Airmass scan (yellow) in the ICI images.

These parameters were built into a clear sky detection method based on multiple binary decision trees that detected pixels that are not clear skies. First, the atmosphere model was calculated using the standard atmosphere model. Then the modeled radiance was subtracted from the measured scene. Pixels with more than $7 \text{ W/m}^2\text{sr}$ are likely clouds and were identified as not clear sky; this is the *radiance mask*. Then an almucantar search was conducted, pixels with an absolute radiance difference more than 10% of the minimum radiance was marked as not clear sky; this was the *angle mask*. Then the gradient of the measured atmosphere scene was calculated along the almucantar scans, along the zenith angle scans, and at a total magnitude. These per-pixel gradient magnitude data were compared to the gradient of the model over a 10×10 pixel sliding region. If the region averaged absolute difference was greater than 20% or $0.0025 \text{ W/(m}^2 \text{ sr)}$ per pixel then the pixels of the region are marked as not clear sky; this was the *gradient mask*. The final binary decision was based on the difference in time. The current

measured scene was subtracted from the previous image and from the next image. If the absolute difference was greater than $0.1 \text{ W}/(\text{m}^2 \text{ sr})$ in either of the difference images then the pixels were marked as not clear sky; this was the *difference mask*. These four masks, radiance, angle, gradient, and difference, were then combined to form a mask of the clear pixels. Any pixel that was not marked in any of these processes are clear sky; this was the *clear sky mask*. The next frame difference requires that the clear sky mask is always one image in the past if used for real-time operation.

These pixels were then saved into history of identified clear sky that contains the x,y coordinates of the pixel, the measured sky radiance, the modeled sky radiance, the zenith and azimuth angles, and the timestamp when the image was collected. During standard operation pixels are removed from the correction if they are more than 4 hours in the past. If the removal time is adjusted so that only pixels from the current image are used, then this algorithm is similar to the algorithms used by other cloud imaging systems (Smith & Toumi 2008; Klebe et al. 2014; Klebe et al. 2015).

Clear Sky Identification by a Support Vector Machine (SVM)

The ICI data processing and similar remote sensing instruments can benefit from recent developments in the computer vision and machine learning communities, in particular the use of a support vector machine (SVM) for data classification. In the ICI3, an SVM was integrated into the data processing routines to build a more advanced version of the adaptive data processing routines. As described in the previous section, the adaptive algorithms started with the assumption that errors in the sky radiance model or

the camera calibration result in a residual radiance image that cannot be used for cloud data collection. The SVM-based approach takes an even more drastic approach and is based on the assumption that there is no accurate sky model and the measured sky radiance may have very large biases that prevent its use for cloud or clear sky detection. Thus the radiometric data cannot be used to identify clouds in the images, and a purely non-radiometric approach must be taken.

SVMs have been applied to a wide variety of remote sensing classification problems, including classification of clouds from satellites.(Mountrakis et al. 2011a; Azimi-Sadjadi & Zekavat 2000; Han et al. 2006). SVM classifiers have been built that used texture data in images to detect objects such as buried targets (Popescu et al. 2012), static groups of people (Manfredi et al. 2014), and malignant tumors (Mavroforakis et al. 2006). Based on this previous work, a similar technique was applied to the LWIR cloud data, incorporating texture information to a classifier that could operate without calibrated camera data. This SVM has the potential to reduce or even remove the reliance of the ICI systems on meteorological data from supporting instruments. However, tests of this approach have only focused on data collected from ARM NSA, so broader accuracy cannot yet be determined.

Support Vector Machines

SVMs are a non-parametric statistical machine learning tool where an arbitrary decision boundary is defined to split data into classes or sets using pre-classified training examples (Burges 1998; Mountrakis et al. 2011b; Lin 2007). In the simplest form, these systems are used to classify $y_i \in \{1, -1\}$, based on a set of features. This dividing line

defines the hyperplane that separates the data so that any point a positive distance from the line is classified as class 1 and any point a negative distance from the line is given a class of -1. The support vectors are the values near the decision boundary that alone specify the decision boundary. Training the SVM is an optimization problem of finding the hyperplane that separates the data (Burges 1998; Lin 2007). This process can be represented by the equation

$$\hat{y}(x) = \mathbf{w}^T \mathbf{x} + b^* = \sum_{i=1}^n y_i \alpha_i \Phi(\mathbf{x}_i)^T \Phi(\mathbf{x}) + b^*. \quad 5 - 6$$

In this equation $\hat{y}(x)$ is the estimate of the class vector y , $\mathbf{w}$ is a weight vector, b^* is an offset term, $\mathbf{x}$ is the matrix of features for the data set, and $\Phi(\mathbf{x}_i)^T \Phi(\mathbf{x})$ represents the inner (dot) product of the feature matrices.

Kernel functions can be used to generalize these algorithms by mapping a non-linear feature space into linear space, where a linear separating hyperplane can be determined. Kernels exploit information about the inner products between data items, and many algorithms can be rewritten so they only require inner products between the inputs. These kernels can be linear, polynomial, radial basis functions, exponential, and various other functions (Burges 1998; Lin 2007). In general, kernels are used to map nonlinear data into a feature space where they are linearly separable. This creates a representation where the inner product is replaced by the kernel function, resulting in the following form:

$$\hat{y}(x) = \mathbf{w}^T \mathbf{x} + b^* = \sum_{i=1}^n y_i \alpha_i \mathbf{K}(\mathbf{x}, \mathbf{x}') + b^*. \quad 5 - 7$$

These classifiers can be further generalized by the introduction of soft margins that allow for the classification of the noisy data encountered in the real world. This is

accomplished by allowing some examples to violate the margin constraints during training (Lin 2007). In the implementation presented later in this paper, the parameter C determines the amount of allowed overlap.

Application to Cloud Remote Sensing SVMs have been applied extensively to a variety of remote sensing problems (Mountrakis et al. 2011a). These applications have included using SVMs to detect cloud cover from thermal imaging data from orbiting satellites, and in these applications they have been successful (Mountrakis et al. 2011b; Azimi-Sadjadi & Zekavat 2000; Mazzoni et al. 2007; Mazzoni et al. 2005). When applied to remote sensing data, SVMs have been shown to have advantages over alternative classification algorithms data, such as consistent identification of the optimal solution and the ability to abstain from assuming a known statistical distribution of the classified data (Mountrakis et al. 2011b). These algorithms also face limitations when applied to remote sensing data, in particular, the selection of the correct kernel function (Mountrakis et al. 2011b).

Much of the work in remote sensing has focused on cloud detection and classification from satellite-based remote sensing systems. Many of these systems have leveraged the multi-spectral data of advanced remote sensing satellites to use in the data classification (Mountrakis et al. 2011b). The ICI instruments provide only band-integrated LWIR radiance over the 8 to 14 μm band, effectively only one spectral channel. Therefore, characteristics were used to provide discrimination between clear sky and clouds relied on texture-based features.

Similar cloud classification systems have been implemented on the GOES and Kalpana-1 satellites to extract cloud occurrence and cloud type data. The classifier for the GOES satellite pixel radiance and standard deviation of 8×8 blocks as inputs into a multi-class hierarchy of nine SVMs to identify 6 cloud types and 3 land surfaces (Azimi-Sadjadi & Zekavat 2000). Cloud classification on the Kalpana-1 satellite used texture features extracted with a Gabor transform as inputs to the SVM (Chethan et al. 2009). In these systems, when different types of kernel functions were explored, linear SVMs were able to provide the highest performance (Chethan et al. 2009). Both of these systems used calibrated cloud radiance as an input parameter, which was not done in the ICI system SVMs.

SVM Implementation in the ICI3

This approach is an extension of the Gradient and Time algorithm described in the previous section. As such, it started in the same manner by identifying regions of the image that had a high probability of being clear sky. Once these regions were identified, a clear-sky model was based on these regions. The difference was that this algorithm did not start with a model of the clear sky radiance. Rather it became based entirely on the uncalibrated sky image and on descriptions of how the image changes in time and across the image. The goal was to use information on how the clear sky was expected to change, or not change, to identify these pixels.

Figure 5-7 shows a flow chart of the SVM implementation on the ICI. First, clear sky pixels were identified from a series of sky images, then these images were used to build a model of the clear sky emission. This model was subtracted from the measured

images, resulting in a residual radiance image used to process the cloud data. This did not require radiometric data until just before the cloud classifier, where any offset biases had been removed and a laboratory gain was sufficient to process these data for clouds.

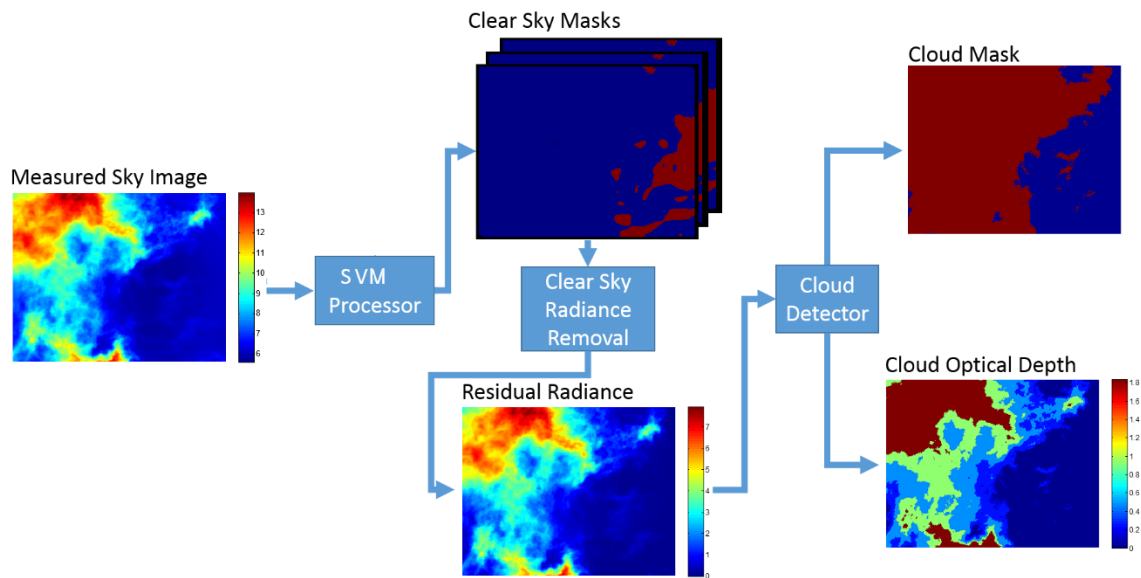


Figure 5-7. The support-vector-machine-based cloud detection method.

Kernel Selection From the literature review it was observed that a simple linear SVM had performed well when applied to cloud cover detection from satellites. For the ICI SVMs, both linear kernels and radial basis functions (RBF) were explored. Testing demonstrated that there might be a slight performance improvement from the RBF kernel; however, this kernel took approximately 28 seconds to classify each pixel in the ICI images, whereas the linear kernel took less than 1 second. It was therefore determined that a linear kernel would be used to process the data from ARM NSA.

Building the Training Dataset To build training data sets for the ICI3 SVM, randomly selected images were hand classified to a set of trained human observers. These

images were classified into five classes: clear sky, thin clouds, thick clouds, mixed clouds (regions of both thin and thick clouds), and errors (closed hatches, partially opened hatches, rain drops, etc). Any regions that were uncertain were left unclassified and were not included in the training or test data. The resulting data set included 689 classified images (~0.1% of the collected images) over 90 randomly selected days dispersed throughout the 557 days the imager operated.

SVM Development These data were initially randomly separated into three subsets. Each was in turn used as a training set with the other two acting as testing sets throughout the algorithm development. After these tests, the data were then resampled into two random sets and the testing repeated.

Initially, 26 parameters were selected for training. These parameters included both radiometric and non-radiometric data mixed with sensor parameter, atmospheric parameter, and image texture data. This allowed the impact of dropping the radiometric parameters to be explored. When exploring the influence of the different parameters on the SVM accuracy, four different metrics were used. The total classification accuracy, which was the percentage of totals pixels placed in the correct class, was attempted to be maximized. The miss-classified cirrus fraction was the fraction of miss-classified pixels that were cirrus (or thin) clouds. This parameter was maximized so that when clouds were miss-classified as clear sky they were not thick clouds. The class loss, which is the fraction of one class placed into another class, was minimized. Clear sky accuracy, which was the fraction of clear sky data that was classified as clear sky, was maximized. As these tests were conducted, 10-fold cross validation was performed on each of the

potential parameter sets. This process retrained and tested the data based on randomly selected subsets of the training and testing data.

Once a SVM had been determined the training and testing data were randomly resampled to produce a new training and testing data sets. With these new data sets, the optimization process was repeated. The new SVM converged to the same set of optimal parameters and produced very similar test results. Therefore, it was determined that these parameters produced a SVM that had sufficient generic performance to be used for cloud detection.

Final Features Selected for the SVM Of the initial 26 features, 10 features were determined from the sky data to be used in training the data. With these features, the SVM provided a total classification accuracy of 93.1% as a two-class classifier identifying clear sky and clouds. When clouds were mis-classified as clear sky, 99.4% of these errors were thin cirrus clouds classified as clear sky. In a 10-fold cross validation of this SVM, a 9.0% class loss was experienced. Some of these values, such as class loss, were higher than expected; however, this SVM was sufficient to be used to identify clear sky pixels as intended.

The features used for this SMV and a brief description are described in Table 5-4. In this table the features are labeled in order of importance to the cloud data classification, based on class-loss in a 10-fold cross validation and a leave-one-out process. In this process, each of the final parameters were dropped from the data and the impact on classification was determined. The relationships between three of these features are shown as 3D scatter plots in Figure 5-8. In this figure the cloud data are

shown as blue dots and clear sky as red circles. From these scatter plots it can be seen in many of these feature sets, that two distinct clusters tend to be formed by the clear sky data and the cloud data.

Table 5-4. Features derived from the sky imagery used in the SVM classification

Feature Name	Description	Increase in Class Loss	Decrease in Accuracy
Sky Digital Number	The raw digital response	2.36 %	3.6 %
Sky Previous Frame Difference Standard Deviation	The spatial 20-pixel disk standard deviation of the difference between the current and next frames	1.00 %	0.36 %
Sky Next Frame Difference	The difference between the current image and the next image	0.60 %	±0.12 %
Sky Next Frame Difference Standard Deviation	The spatial 20 pixel (disk) standard deviation of the difference between the current and next frames	0.041 %	±0.35 %
Almucantar Stats Standard Deviation	The standard deviation of the data in each almucantar scan in 1 degree bands	0.32 %	±0.08 %
Sky Entropy	The entropy filter in the image over a 4 pixel diameter disk	0.12 %	±0.01 %
Sky Gradient	The magnitude of the gradient of the sky	0.04 %	±0.01 %
Sky Radial Image	The sky image divided by the minimum of each almucantar scan in 1 degree bands	0.03 %	±0.01 %
Zenith Angle Gradient	The portion of the gradient projected along a vector that points to the zenith at each pixel	0.02%	±0.01 %

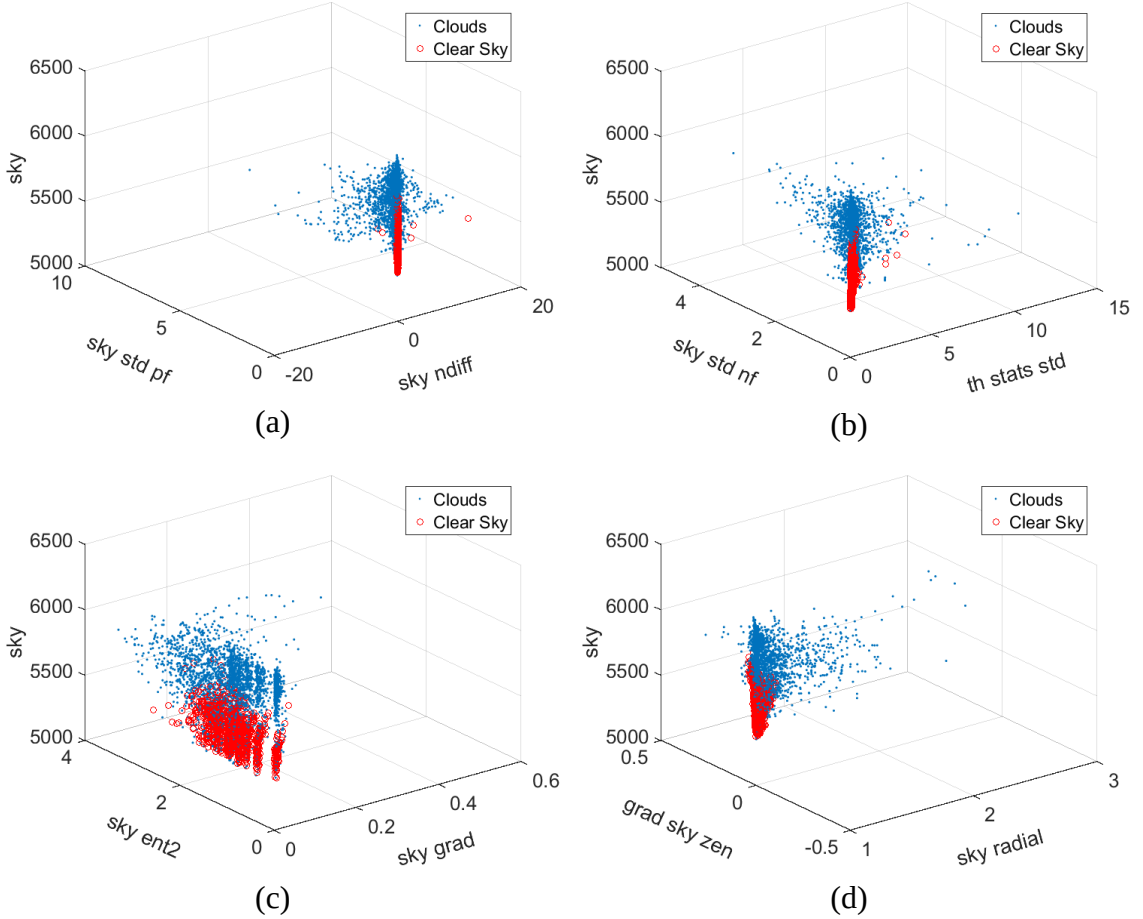


Figure 5-8. The hand-selected cloud (blue dots) and clear sky (red o's) data used as training data shown in 3D scatter plots for three features at a time. The total dataset had 12 features.

These features were non-radiometric image parameters and image texture. Within these tests, the most critical parameter was the raw sky image. If residual radiance L_{rr} , or calibrated sky radiance L_{sky} were used in place of the raw sky, the SVM accuracy increased in accuracy by approximately 2%. It was deemed that this slight decrease in accuracy was acceptable to achieve the project goal of a fully self-contained instrument for remote deployments.

This SVM does have a non-negligible probability of triggering on thick clouds, rain drops, and hatch errors. In this following descriptions the standard cloud classifier for each pixel will be referred to as $S_c(x, y)$. To add further discrimination to the clear sky two methods were used. The first method was to produce two additional SVMs, one that discriminated just between clear sky and thick clouds, referred to as the clear versus thick SVM or $S_{cvt}(x, y)$, and one that discriminated between normal data and error data (raindrops, hatch errors) referred to as the error SVM $S_{err}(x, y)$. Then pixels were labeled as clear sky based on a the logical statement shown below

$$Clear(x, y) = S_c(x, y) + S_{cvt}(x, y) + \overline{S_{err}(x, y)}. \quad 5 - 8$$

The second method was a ten-times-bagging method in which ten clear sky SVMs were produced from random samples of the training set and then all ten were applied to the data. When eight or more of these SVMs agreed that a pixel was clear sky, then the sky was considered clear.

Cloud Classification with a SVM

After the development of a clear sky classifier with the SVM, a second classifier was built that used a multi-class SVM to identify and classify clouds. This system was based on seven SVMs that were combined in a decision tree that led to identification of clear sky, four thin cloud levels, and thick clouds.

First the cloud image was initialized as thick clouds; a value of 5. Then, if the all-versus-thick SVM did not report thick clouds, the cloud image pixel is set to 4. Then pixels where the clear-versus-thick SVM reported not thick were set to 3. Then pixels where the thin-cloud SVM reported clouds were set to 2. Pixels where the very-thin-cloud

SVM reported clouds were then set to 1. Finally, pixels where the clear sky data $Clear(x, y)$ is true were set to 0. This produced a SVM-only classified cloud image.

Validating the Cloud Classification Algorithms

With a developed set of processing routines and supporting models, these parameters needed to be validated with experimental data. This validation took place using the data from the ICI3 deployment at the ARM NSA site in Barrow, AK, along with testing on other instruments. Comparisons between these different algorithms and comparisons with other co-located cloud imagers follows in Chapter 7.

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INSTRUMENT ACCURACY

Cloud Detection Accuracy

This chapter addresses the question of how the ICI3 performs as a cloud detection system. Uncertainties in the data used in the cloud detection algorithms led to a minimum detectable cloud signal for each of the data processing algorithms. The data produced by the ICI3 was sensitive to these uncertainties; therefore, to quantify this uncertainty a combination of error propagation and a Monte Carlo system analysis was performed. This analysis included uncertainties drawn from Chapter 4 and Chapter 5. This analysis was conducted assuming thin cirrus clouds, since the signal from these clouds is close to that of the atmosphere and it was detecting these clouds where system uncertainty plays the most significant role.

Uncertainty in the Cloud Data Processing

Uncertainties in the data used to process the ICI3 data lead to uncertainties in the cloud data product. Understanding these uncertainties can lead to an understanding of the detection accuracy and sensitivity of the ICI instrument. These uncertainties exist both in the ICI3 instrument and in the external data used in the cloud detection algorithms. Figure 6-1 shows the standard data processing flow for the cloud detection process with the three main sources of uncertainty highlighted. There are three main sources of uncertainty in this process, the camera calibration (red outlined box), the simulated sky imagery (blue outlined box), and the cloud detection thresholds (brown outlined box).

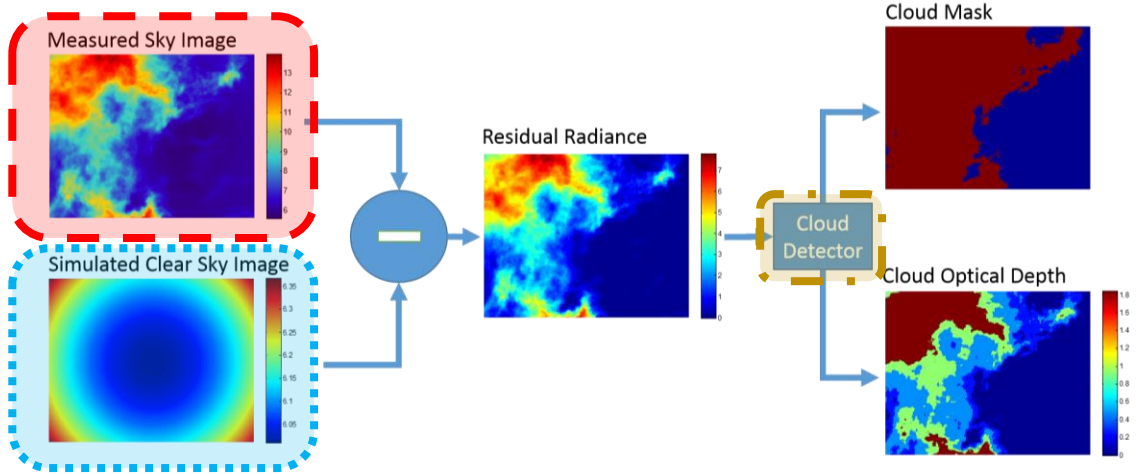


Figure 6-1. the standard data processing flow for the cloud detection process with the three main sources of uncertainty identified: the camera calibration (red outlined box), the simulated sky imagery (blue box), and the cloud detection thresholds (brown box).

Uncertainty in the Measured Signals The combined effects of the uncertainties can be described as a discrete random variable added into the signals from the atmosphere (clear sky) or atmosphere and cloud (cloudy sky). In this case the radiance detected by a single pixel in the camera, $L_A[n]$, becomes a combination of the sky radiance signal, $a[n]$, with a random variable $W[n]$ that contains both the noise and uncertainty in the camera signals.

$$L_A[n] = a[n] + W[n] \quad 6 - 1$$

When a cloud is present, the detected radiance $L_C[n]$ becomes a combination of the sky radiance signal $a[n]$, the signal from the cloud $c[n]$, and the random variable $W[n]$. Since cirrus clouds have the lowest emission, these clouds will be closest to the limit of detectability; therefore, $c[n]$ should be considered the signal from a cirrus cloud.

$$L_C[n] = a[n] + c[n] + W[n] \quad 6 - 2$$

Uncertainty in the Atmosphere Model All three of the ICI3 data processing routines required the atmosphere to be modeled. These routines just differ in how this model was obtained. Each of these atmosphere models had an associated uncertainty that can be described by the introduction of a random variable, $X[n]$. The modeled atmosphere signal $L_M[n]$, then becomes a combination of the modeled atmosphere radiance $a_m[n]$ and this random variable.

$$L_M[n] = a_m[n] + X[n] \quad 6 - 3$$

Uncertainty in the Residual Radiance In the data processing, this modeled signal, $L_M[n]$, was removed from the measured sky signal, $L_A[n]$. It was assumed that the modeled atmosphere radiance signal $a_m[n]$ was unbiased and therefore equal to the sky radiance signal $a[n]$. The result is a residual radiance signal that had zero mean when no cloud was present and non-zero mean when a cloud was present. This can be described by the following equations, where the residual signal $L_{Arr}[n]$ is the difference of the two random variables $W[n]$ (uncertainty in the camera) and $X[n]$ (uncertainty in the atmosphere model) when no cloud was present.

$$L_{Arr}[n] = (a[n] + W[n]) - (a_m[n] + X[n]) = W[n] - X[n]. \quad 6 - 4$$

The cloud biasing signal $c[n]$ is added to these random variables when a cloud is present.

$$\begin{aligned} L_{Crr}[n] &= (a[n] + c[n] + W[n]) - (a_m[n] + X[n]) \\ &= c[n] + W[n] - X[n] \end{aligned} \quad 6 - 5$$

The difference between $W[n]$ and $X[n]$ can be described by another random variable $Z[n]$.

If we assumed both $W[n]$ and $X[n]$ are zero-mean, independent, Gaussian random variables, then $Z[n]$ is a zero-mean, Gaussian random variable.

$$\mathbf{Z}[n] = \mathbf{W}[n] - \mathbf{X}[n] \quad 6 - 6$$

Hypothesis Testing Approach to Cloud Detection Based on the previous analysis, the cloud detection problem was cast into a standard hypothesis testing approach. Cloud detection was then based on deciding between the null hypothesis H_0 (no cloud) or the alternative hypothesis H_1 (cloud) based on the measurements $L_{Arr}[n]$. In this situation our signals were

$$H_0: L_{Arr}[n] = \mathbf{Z}[n], \quad 6 - 7$$

and

$$H_1: L_{Crr}[n] = c[n] + \mathbf{Z}[n]. \quad 6 - 8$$

This was simplified further to the optimal test for two hypotheses with equal variances and different means. In this case, the probability distribution f of residual radiance L_{rr} that describes both a clear pixel and a cloudy pixel became

$$f(L_{rr}|H_0) = \frac{1}{\sigma\sqrt{2\pi}} \exp\left(-\frac{x^2}{2\sigma^2}\right). \quad 6 - 9$$

The cloudy pixel was collected at the same time and therefore had the same variance σ^2 , just offset by the cloud signal c , so the probability distribution became

$$f(L_{rr}|H_1) = \frac{1}{\sigma\sqrt{2\pi}} \exp\left(-\frac{(x-c)^2}{2\sigma^2}\right). \quad 6 - 10$$

In this binary hypothesis testing problem the decision to reject the null hypothesis was based on a decision threshold γ . The situation where the sky was clear but L_{rr} was greater than the decision boundary was a statistical Type 1 error (false positive). This probability is given by 1 minus the cumulative distribution function (CDF) of f given H_0 up to γ and is described by

$$P(L_{rr} > \gamma | H_0) = 1 - \frac{1}{2} \left[1 + \operatorname{erf} \left(\frac{\gamma}{\sigma\sqrt{2}} \right) \right]. \quad 6 - 11$$

Type 2 errors (false negatives) occur when clouds are present but L_{rr} is less than γ . The probability of this Type 2 error is the CDF of f given H_1 up to γ ,

$$P(L_{rr} < \gamma | H_1) = \frac{1}{2} \left[1 + \operatorname{erf} \left(\frac{\gamma - c}{\sigma\sqrt{2}} \right) \right]. \quad 6 - 12$$

The optimal detection threshold was placed halfway between c and 0, or $\gamma = c/2$. In this case, the probability of detection became based on the signal-to-noise ratio. It is critical to note that, in this case, noise is defined as the total system uncertainty, not to be confused with the noise-equivalent radiance derived previously.

$$SNR = \frac{c}{\sigma} \quad 6 - 13$$

In this case, the probability that a clear sky will have a signal greater than γ is

$$P(L_{rr} > \gamma | H_0) = 1 - \frac{1}{2} \left[1 + \operatorname{erf} \left(\frac{SNR}{2\sqrt{2}} \right) \right] \quad 6 - 14$$

and the probability that a given cloud will have a signal less than γ is

$$P(L_{rr} < \gamma | H_1) = \frac{1}{2} \left[1 + \operatorname{erf} \left(-\frac{SNR}{2\sqrt{2}} \right) \right]. \quad 6 - 15$$

To illustrate this, a series of cloud and clear sky signals were calculated with a hypothetical system uncertainty of $\sigma = 0.5$ described by a Gaussian random variable. The cloud signal c was increased to give different signal to noise ratio (SNR) values, the decision boundary γ was placed as half of the cloud signal or $c/2$ point where the two distributions overlap. Results are shown in Table 6-1 and Figure 6-2 illustrates this problem, where the clear sky is a blue zero-mean distribution and the cloudy signal is the red no-zero distribution. In the scatter plots on the right, both data sets have been

displayed with the same symbol and color to illustrate why it is difficult to differentiate between the two signals.

Table 6-1. Results of hypothetical cloud and clear sky detection.

SNR	σ (W/m ² sr)	c (W/m ² sr)	γ (W/m ² sr)	$P(L_{rr} > \gamma H_0)$	$P(L_{rr} < \gamma H_1)$
1	0.5	0.5	0.25	30.9%	30.9%
2	0.5	1	0.5	15.9%	15.9%
3	0.5	1.5	0.75	6.7%	6.7%
4	0.5	2	1	2.3%	2.3%
5	0.5	2.5	1.25	0.6 %	0.6 %

As can be seen in the tabular results and in the figures, if the threshold is set too close to zero, the probability of a Type 1 error becomes high and a clear sky will be reported as clouds in up to 30% of the instances. To have an accurate cloud detector, the number of false positives or Type 1 errors must be kept low. To ensure the false positive rate is low in the ICI3, an SNR of 5, or less than 1% probability of a false positive, was used as the minimum cloud classification threshold. To make this work, the sources and level of uncertainty in the system had to be understood.

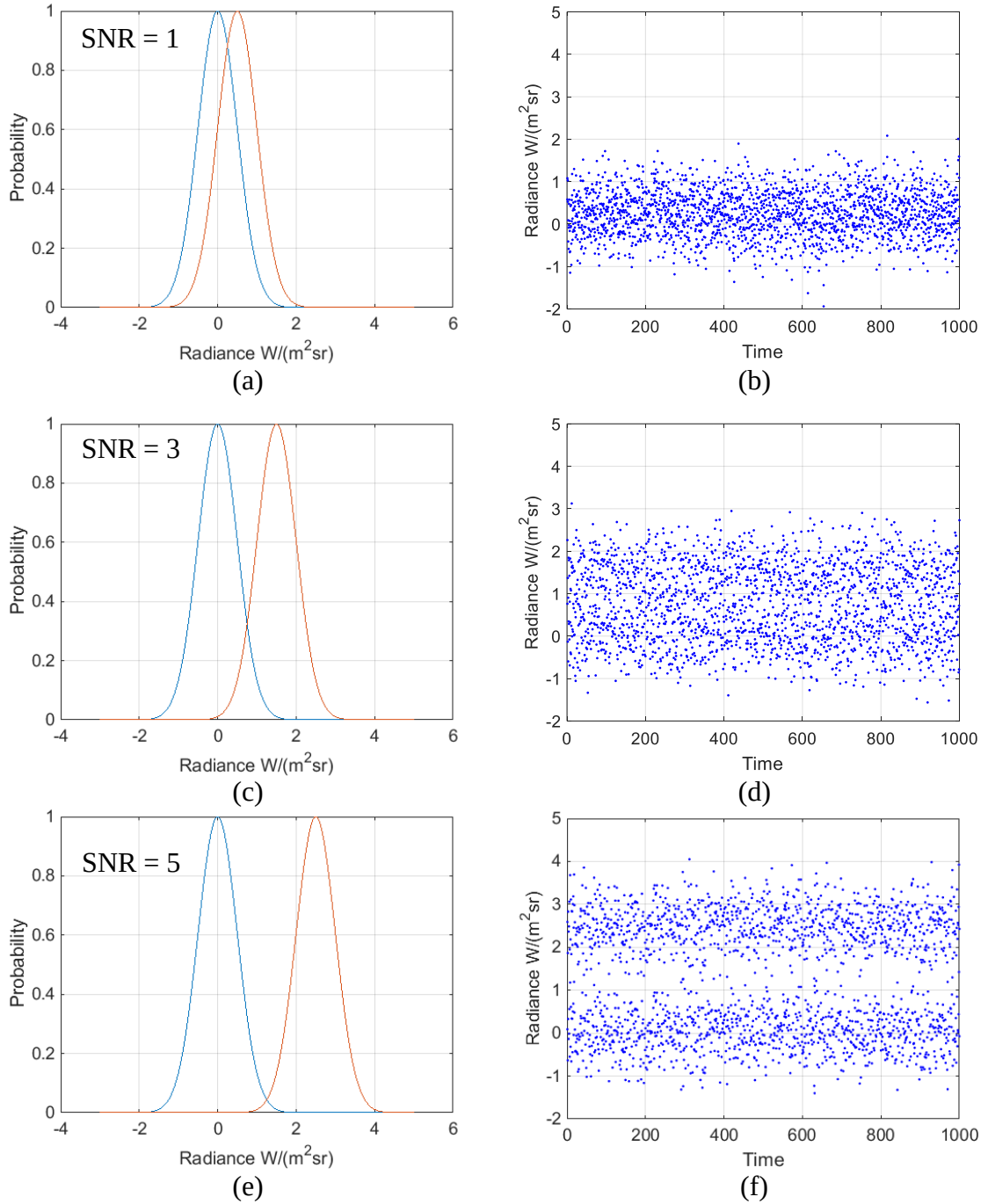


Figure 6-2. Detecting the difference between a zero-mean Gaussian random variable and a nonzero-mean Gaussian random variable with the same variances. Clouds with a residual radiance similar in size to the uncertainty in the system (a) and (b) cannot be reliably detected. As the signal-to-noise increases, reliable detection of the cloud increases.

Uncertainty in the Atmosphere Model

Owing to the complicated processing that goes into deriving the atmosphere model, a Monte Carlo approach was used to understand how errors in the input parameters impacted the output modeled sky radiance. There are three main inputs to the atmosphere model: surface radiance (derived from surface temperatures); precipitable water vapor; and zenith angle of each pixel. Each of these parameters has an associated uncertainty, specified by instrument operator. The uncertainties in the meteorological instruments can be found in the NSA Barrow Meteorological Tower User's manual (Ritsche 2011), and the ARM Surface Meteorology Systems Handbook (Larsen 2011). The uncertainty in the precipitable water vapor measurements from the Microwave Radiometer are summarized in the Microwave Radiometer Profiler Handbook (Liljegren 2002). These values are summarized in Table 6-2. The distribution of these errors are not specified within the instrument documentation; therefore, for the following analysis it has been assumed they have a Gaussian distribution. The range of these atmosphere model parameters experienced during the ARM NSA deployment is shown in Figure 6-3 (Holdridge & Kyrouac 2015).

Table 6-2. Uncertainty in the atmosphere model parameters

Parameter	Range	Uncertainty	Resolution
Instrument Alignment	0° to 55°	±1 °	NA
Precipitable Water Vapor (MWRP measurement)	0 cm to 3 cm	±0.01 cm	
Surface Temperature (ARM MET Station)	-43 °C to 20 °C	±0.05 °C	0.001 °C

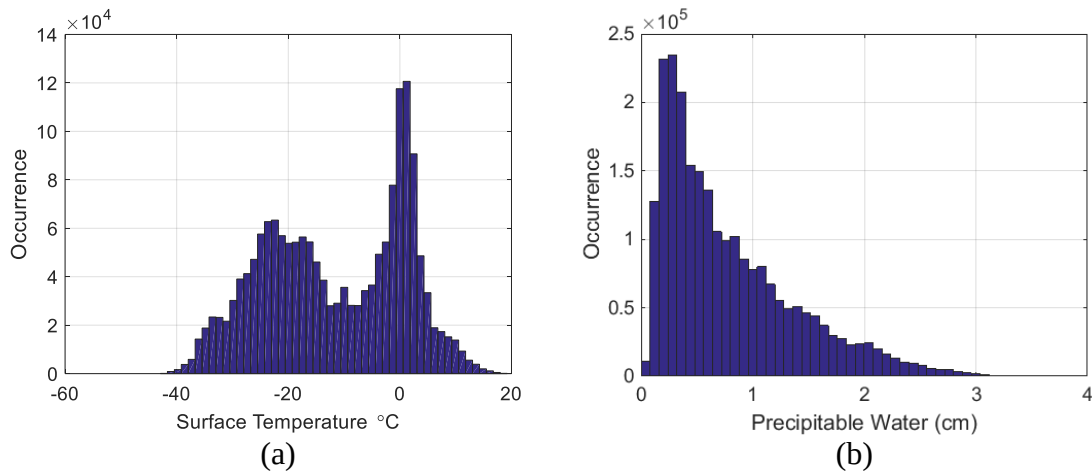


Figure 6-3. The atmosphere environment experienced by the ICI3 during deployment at the NSA site: (a) near surface air temperature and (b) precipitable water vapor.

Atmosphere Model Parameters

These measurements were used to produce 100 pairs of surface temperature and PWV that covered the full range experienced at ARM NSA. Then to simulate the error a Gaussian distribution with the standard deviation specified in Table 6-2 was added to the temperature at each pair. This produced 100 new measurement pairs. Next, a simulation was run using each of these measurements and the standard deviation of the resulting models was recorded at each angle throughout the field of view. This process was repeated for each temperature-PWV pair with the error added to the PWV measurements. The resulting atmosphere model uncertainties are shown in Figure 6-4 for zenith angles of $\theta = 0^\circ$, $\theta = 20^\circ$, and $\theta = 40^\circ$.

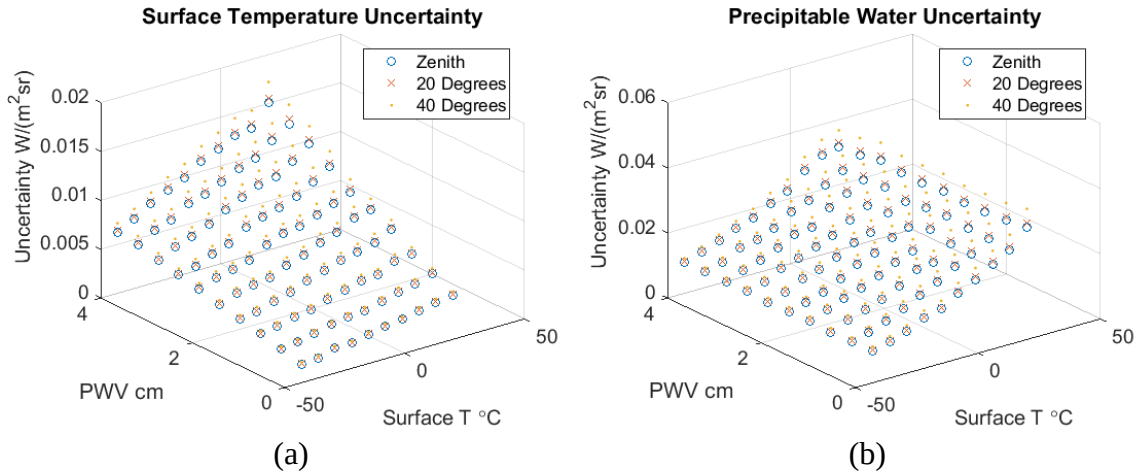


Figure 6-4. The Monte Carlo atmospheric radiance uncertainty model for three zenith angles ($\theta = 0^\circ$, $\theta = 20^\circ$, and $\theta = 40^\circ$) over the expected range of air temperature and precipitable water vapor arising from (a) radiance uncertainty in the air temperature measurement and (b) uncertainty in the precipitable water vapor measurement.

The majority of the radiance uncertainty arose from the uncertainty in the PWV, with a maximum uncertainty nearly four times greater than the maximum uncertainty from surface temperature. The covariance of these parameters was found to be less than 10^{-8} and therefore they have been assumed to be independent. These surface temperature-PWV and uncertainty sets were used to produce a look up table that could be used to produce an estimate of ICI3 atmosphere model uncertainty for any image collected during the deployment at NSA. Two examples of these error estimates are shown in Figure 6-5. In (a) 1000 random measurement pairs of surface temperature and PWV have been input into this model for a zenith angle of 0° . In (b) a single pair at a specific time has been used to estimate the error across the entire instrument field of view.

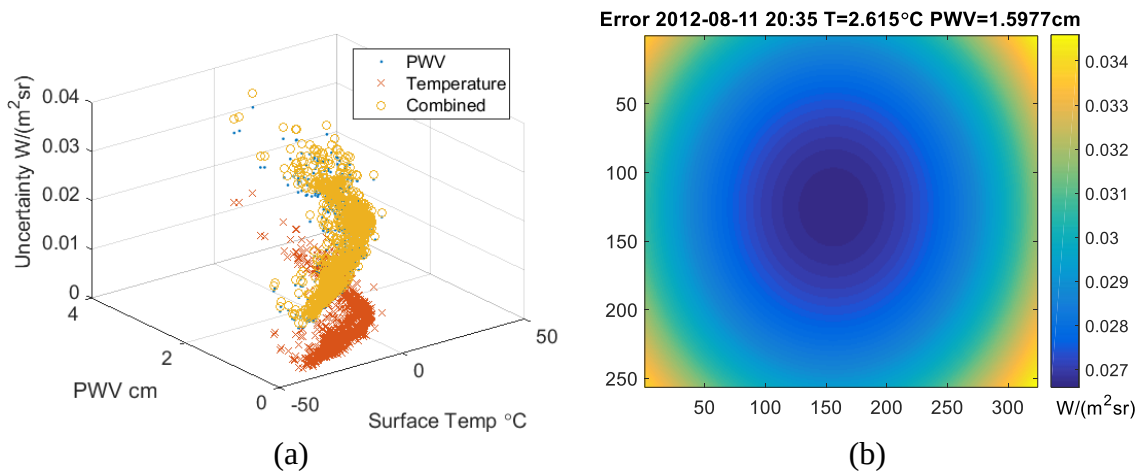


Figure 6-5. Example application of the atmosphere uncertainty model. (a) Radiance uncertainty for 1000 random pairs of precipitable water vapor and air temperature experienced during the NSA deployment and (b) the radiance uncertainty across the FOV experienced for a specific measurement.

Uncertainty Due to the Field of View

The second source of uncertainty in the atmosphere model was the error in matching a given pixel with the correct zenith angle. These errors occur from imperfect field of view mapping, shown to be less than 0.2° across the full field of view (see Chapter 4), and imperfect instrument pointing. For the purpose of this uncertainty model it was assumed that the misalignment of the ICI system dominates the field of view uncertainty, and this error has been estimated as a Gaussian with a $\pm 1^{\circ}$ standard deviation. After the ICI3 was installed, the system was leveled and the camera positioning system was tested. Every time it was serviced, this alignment changed. Additionally, it was observed that under strong winds the instrument housing would shift, changing the camera pointing. The tightness of the straps holding the ICI3 to the instrument deck at ARM NSA also shifted the box.

To understand the effect of this $\pm 1^\circ$ error on the system, 100 pairs of temperature and PWV data were selected to cover the expected range of atmosphere inputs. The angle parameters in the model were combined with a Gaussian random variable with a 1° standard deviation. The atmosphere simulation was then run for each of the shifted angles and the deviation in the output radiance was observed. The result of this over the full range of temperature inputs and three zenith angles is shown in Figure 6-6.

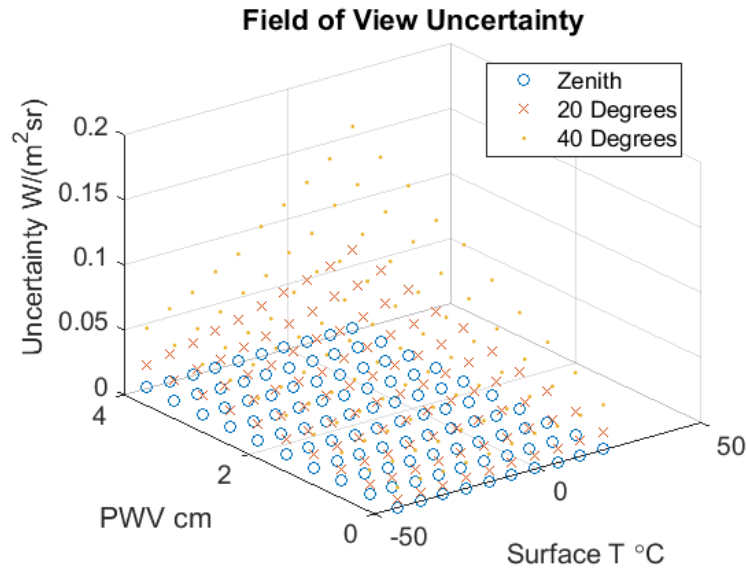


Figure 6-6. The Monte Carlo radiance uncertainty model based on $\pm 1^\circ$ random errors caused by misalignment of the ICI system. Note the impact of the error increases with zenith angle.

These data were used to produce a lookup table that were used to estimate the atmosphere model radiance uncertainty arising from pixel misalignment. Figure 6-7 shows this estimate for 1000 surface temperature and PWV observations at three zenith angles, and the error calculated for a specific surface temperature and PWV across every zenith angle in the imager's field of view.

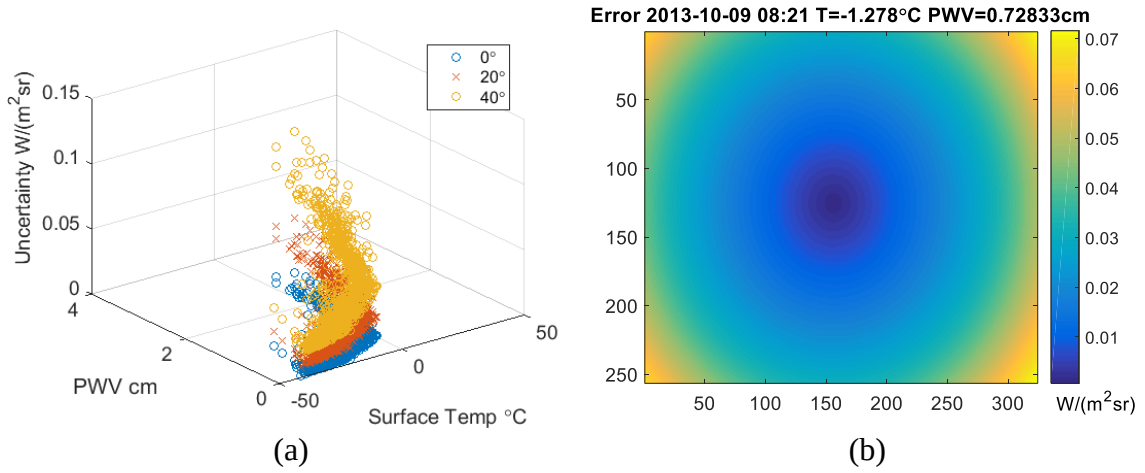


Figure 6-7. Example application of the field of view uncertainty model: (a) uncertainty for 1000 random pairs of surface temperature and air temperature experienced during the NSA deployment and (b) the uncertainty across the FOV experienced for a specific measurement.

ICI3 Atmosphere Model Accuracy

The errors present in the ICI3 atmosphere models were combined to produce an estimate of the radiometric root mean square error in the atmosphere model, $RMSE_a$. This was calculated for each pixel in each image collected during the deployment of the ICI3. It was assumed that the atmosphere errors were independent, so they were added together in terms of their variances, resulting in the equation

$$RMSE_a^2 = \sigma_K^2 + \sigma_{pwv}^2 + \sigma_{FOV}^2. \quad 6 - 16$$

In this equation, σ_K is the atmosphere model uncertainty dependent on the uncertainty in the surface temperature measurements, σ_{pwv} is the uncertainty dependent on the precipitable water vapor measurements, and σ_{FOV} is the uncertainty dependent on the alignment of the imager with the zenith so that the camera optical axis was pointed at the zenith.

Uncertainty in the Radiometric Calibration

The largest source of uncertainty in the ICI3 system was the uncertainty in the data calibration. The calibration process described in Chapter 4 resulted in a very accurate camera calibration; however, there was still uncertainty present in the resulting data. The residual uncertainty in the FPA-temperature-corrected data are presented in Table 6-3, showing both variation of a pixel in time σ_t and pixel-to-pixel variation across the focal plane array σ_s , along with a radiance bias L_b in the calibration.

Table 6-3. Summary of the calibration accuracy

Calibration	σ_t (time)	σ_s (spatial)	Combined σ_r	Calibration Bias L_b
FPA-Temp Corrected	0.27 W/(m ² sr)	0.067 W/(m ² sr)	0.28 W/(m ² sr)	-0.09 W/(m ² sr)

Additional Sources of Uncertainty

Additional uncertainties may be dependent on the ICI3 environment or on changes in this environment, changes in camera operation, and other aspects of the ICI3 system. The following sections explore these additional sources of uncertainty and describe a dynamic camera uncertainty model that can be used to estimate the radiometric uncertainty in any image collected by the ICI during deployment.

Dynamic Changes in the Calibration Uncertainties In the ICI3 the radiometric uncertainties have been observed to change based on the FPA-temperature. Two of the parameters shown in Table 6-3, the spatial standard deviation and calibration bias, were found to depend on the dynamics of the camera. This requires that the range of FPA-

temperatures experienced by the camera must be understood. The camera FPA temperature and rate at which the FPA temperature changed is shown in Figure 6-8.

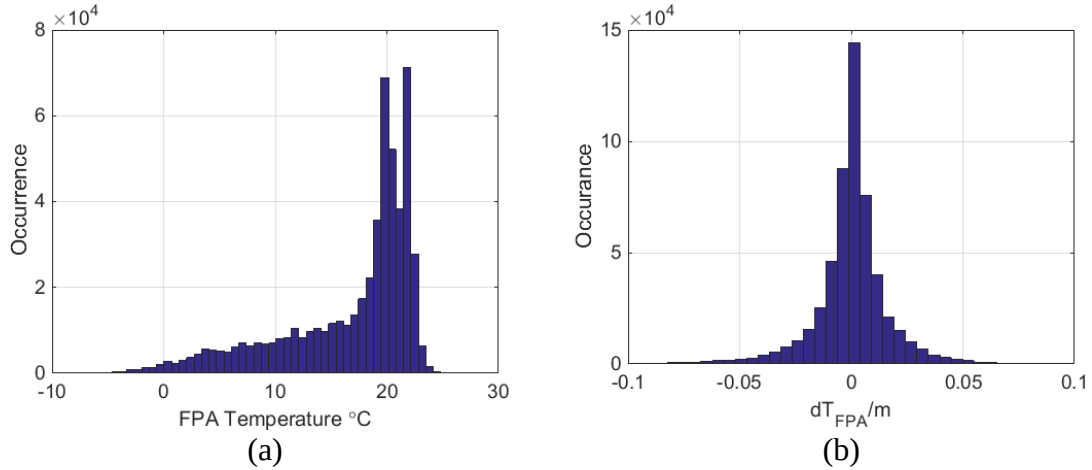


Figure 6-8. The environment experienced by the ICI3 LWIR camera: (a) camera FPA temperature and (b) rate of FPA temperature change.

The spatial radiance uncertainty was found to change based on the difference between the FPA self-emission (radiance from a blackbody at the FPA-temperature) and the scene radiance (ΔL) and based on the rate change of the FPA temperature. The calibration bias L_b (deviation from zero mean error) was found to vary based on the rate of FPA-temperature change. Figure 6-9 (a) shows σ_s as a function of ΔL for two different rates of FPA-temperature change. Figure 6-9 (b) shows how the calibration bias changed based on the rate of FPA-temperature change.

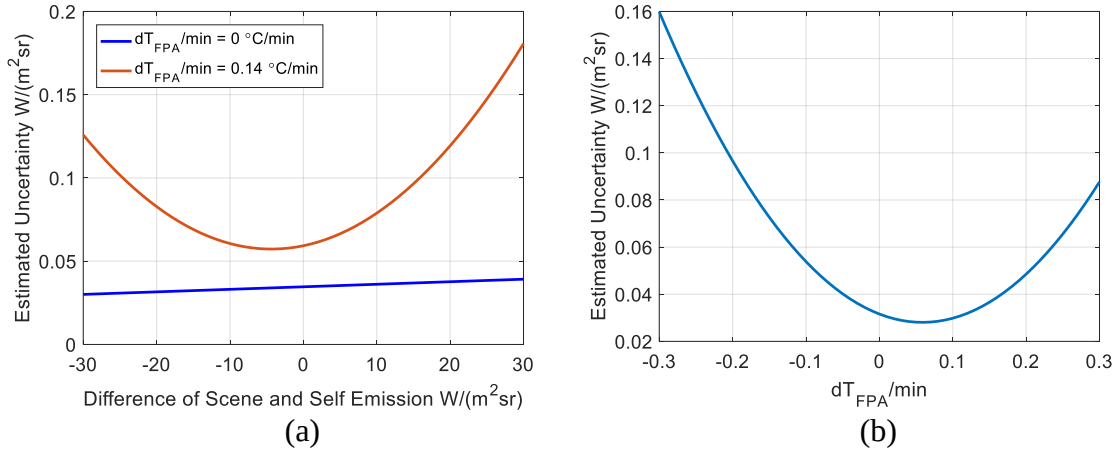


Figure 6-9. (a) The estimated radiance uncertainty with the difference between FPA self-emission and scene radiance $\sigma_s(\Delta L, dT/dt)$ for two different rates of FPA temperature change and (b) the calibration bias based on rate of FPA temperature change.

Calibration Uncertainties Due to Extrapolation The brightness temperature of the expected sky scenes was as low as $-80 \text{ } ^\circ C$ ($4 \text{ W}/(m^2 \text{ sr})$), well below what could be achieved with the equipment available at MSU. The blackbody used for the camera calibration only has an operating range from $0^\circ C$ to $100^\circ C$ [$30 \text{ W}/(m^2 \text{ sr})$ to $120 \text{ W}/(m^2 \text{ sr})$]. In practice, $5 \text{ } ^\circ C$ [$32.5 \text{ W}/(m^2 \text{ sr})$] was the lowest temperature used, to avoid any possibility of frost or condensation on the blackbody surface. To avoid excessive heating of the camera $60 \text{ } ^\circ C$ [$75 \text{ W}/(m^2 \text{ sr})$] was the highest temperature used. Thus, extrapolation was inherently taking place from the laboratory or in-field blackbody measurements to the cold sky scenes. In terms of radiance, the range of extrapolation from the lowest blackbody reference was $\sim 66\%$ of the difference between the highest and lowest blackbody references. This process has been shown to be reliable owing to the linear response of thermal detectors such as microbolometers (Han et al. 1997; Knuteson et al. 2004); however, this is an added source of uncertainty.

To understand this uncertainty, the calibration data from the center 5 degrees of the ICI3 field of view was randomly resampled and the variation in the calibration determined. These pixels were selected because they are the pixels that were used later to compare with co-located zenith-viewing instruments at ARM NSA. This recalibration selected 1% of the calibration data for 1000 iterations. These new calibrations were used to calibrate a set of data and the resulting error was determined. This allowed for the estimation of the radiance fractional error with scene radiance, as shown in Figure 6-10.

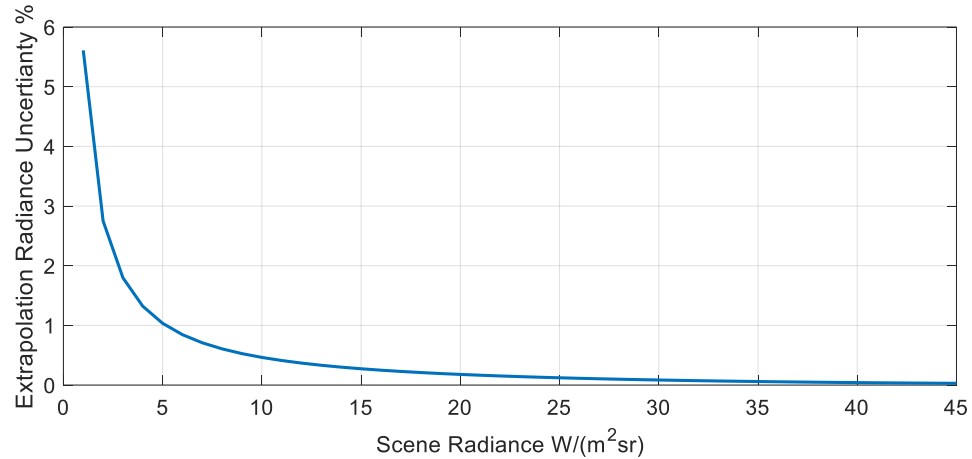


Figure 6-10. The estimated extrapolation-based uncertainty with scene radiance α_e based on the range of scenes experienced during the Barrow AK deployment.

From these data a look up table was built that allowed estimation of the extrapolation fractional error Δ_e based on the calibrated scene radiance L_s . The standard deviation uncertainty was then estimated from

$$\sigma_e = \frac{\Delta_e(L_s)L_s}{100\%}. \quad 6 - 17$$

Bandwidth-Dependent Uncertainty The uncertainty in the shape of the camera's spectral response (summarized here as “bandwidth”) leads to another source of error in

the ICI3 instrument. By calibrating a series of example data with each spectral response from the genetic algorithm, an uncertainty estimate was derived. This uncertainty as a percent of the scene radiance is shown in Figure 6-11.

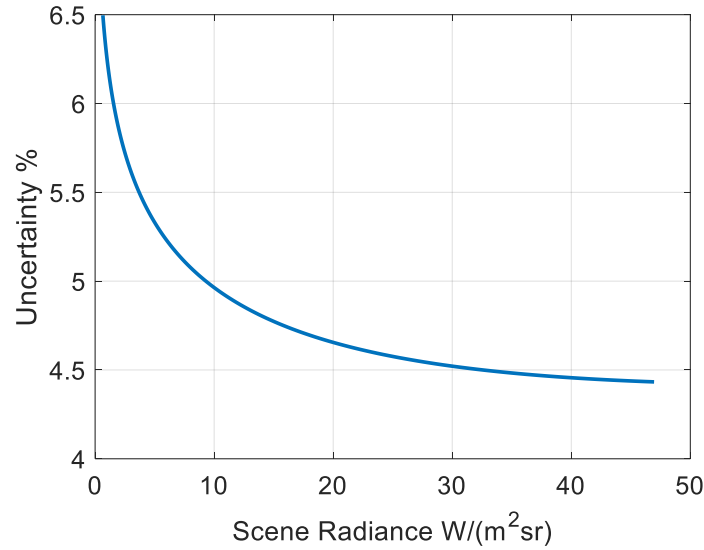


Figure 6-11. The calibrated radiance uncertainty that results from the uncertainty in the genetic-algorithm-derived spectral response.

These data were used to build a lookup table of bandwidth-dependent fractional uncertainty based on the scene radiance. This resulted in a bandwidth dependent uncertainty σ_b described by

$$\sigma_b = L_s \frac{\Delta_b(L_s)}{100\%}. \quad 6 - 18$$

FFC-Dependent Uncertainty During normal operation the ICI3 periodically performed a flat field correction (FFC). During this correction an image was collected while the internal shutter was closed and the pixel biases were updated to produce a flat image of the shutter. This process happened internal to the camera and was required for

the Photon camera to produce good imagery. There was an uncertainty added to the imagery because of these bias adjustments. To study this in the ICI3, the FFC was only performed when the camera was observing the blackbody. An image of the blackbody was collected just before the FFC, then again just after the FFC. This allowed the effect of these bias changes on the radiometric imager to be studied. Figure 6-12 shows the difference between the pre-FFC and post-FFC blackbody images. In (a), the histogram of these differences is shown. In (b), the RMS value of the uncertainty across the focal plane array is shown.

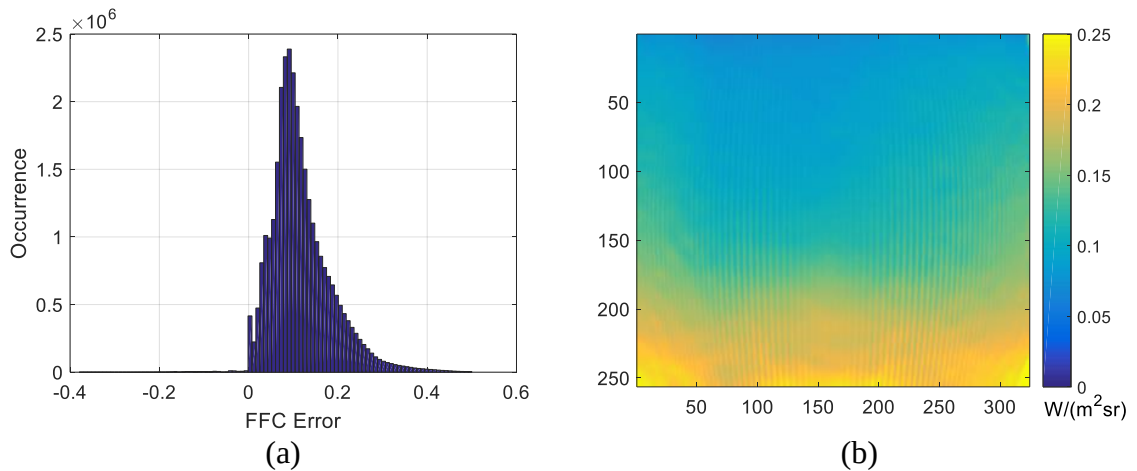


Figure 6-12. Uncertainty in the images caused by changes that occur during a FFC: (a) histogram of the differences between blackbody images before and after a FFC and (b) the RMS value of the uncertainty across the focal plane array.

These bias adjustments lead to a significant source of radiometric uncertainty for the ICI.

The RMS value of this error is $\sigma_{FFC} = 0.1365 \text{ W}/(\text{m}^2\text{sr})$, with a strong spatial variation, with the error nearly 5x stronger near the bottom of the focal plane array compared to the top of the array.

These errors are caused by periodic drifts in the camera that happen between FFCs and relate back to the scenes observed during the FFC period. Figure 6-13 shows two difference images for different time periods on the same day. In (a) the FFC period has viewed scenes of thick clouds and the noise is uniform with an root mean square (RMS) value of $0.0891 \text{ W}/(\text{m}^2\text{sr})$. In (b) the FFC period included changing scenes of thin clouds and clear sky and the noise shows distinct banding with an increased RMS value of $0.1073 \text{ W}/(\text{m}^2\text{sr})$.

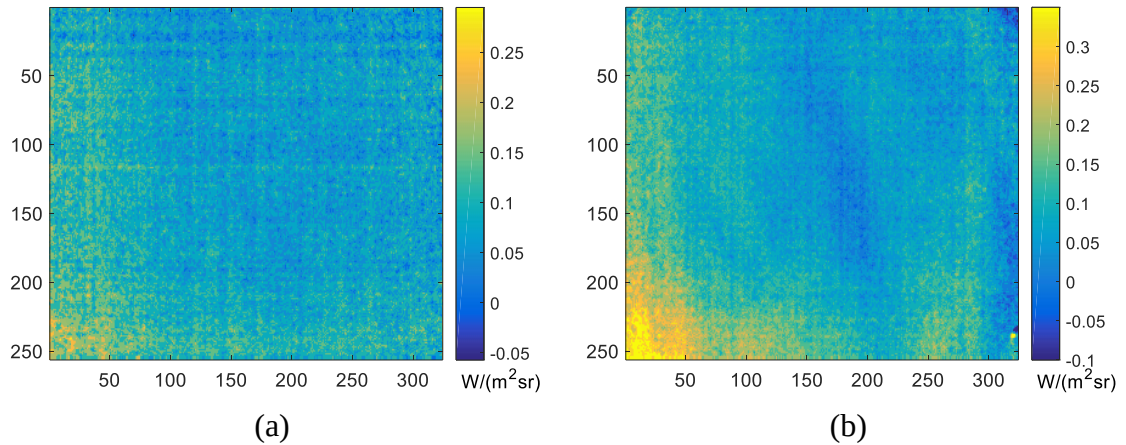


Figure 6-13. Two difference images from different FFC periods on the same day. In (a) the FFC period had a scene of thick clouds and the noise was low and uniform. In (b) the FFC period had a changing scene of thin clouds and clear sky and the noise showed distinct banding.

Although these drifts may be periodic and it may be possible to predict them, these changing patterns due to the observed scenes made it difficult to build a predictor of these errors for a given pixel at a given time. In the ICI3 there was no attempt to correct for this effect and, therefore, the FFC errors were considered a random error.

ICI3 Calibrated Measurement Accuracy

The ICI3 calibration error can be combined with each of the previously described sources of additional error to produce an estimate of the radiometric root mean square error, $RMSE_c$ for each image collected during the deployment of the ICI3. If it is assumed that these errors are independent, then they can be added together in terms of their variances, resulting in the equation

$$RMSE_c^2 = \sigma_t^2 + \sigma_s^2 + \sigma_b^2 + \sigma_e^2 + \sigma_{NER}^2 + L_b^2, \quad 6 - 19$$

where σ_t is the temporal standard deviation in the radiometric calibrated data, σ_s is the spatial standard deviation in the radiometric calibrated data, σ_b is the estimated bandwidth based uncertainty, σ_e is the uncertainty due to the calibration extrapolation, and σ_{NER} is the NER of the camera. Inserting the models for σ_s , σ_b , and σ_e leads to the equation

$$RMSE_c^2 = \sigma_t^2 + \sigma_s \left(\Delta L, \frac{dT}{dt} \right)^2 + \left(L_s \frac{\Delta_b(L_s)}{100\%} \right)^2 + \left(L_s \frac{\Delta_e(L_s)}{100\%} \right)^2 + \sigma_{NER}^2 + \sigma_{FFC}^2. \quad 6 - 20$$

From these equations, the uncertainty can be estimated for each pixel of each cloud image collected during the ARM NSA deployment of the ICI3. This uncertainty is the random variable $\mathbf{W}[n]$ in equation 6 - 1.

Application of the ICI Uncertainty Models

With the previously described uncertainty specific to the ICI3, there was sufficient information to address the questions of instrument accuracy and the minimum detectable cloud in the ICI systems. The different uncertainty parameters that exist in the

camera and the atmosphere model were shown in Table 6-4. For the parameters that are measured and expected to remain constant, independent of the scene radiance, the radiometric value of the uncertainty has been noted in $W/(m^2 sr)$. The source and how the parameter changes with the scene or the environment have also been noted. This resulting system accuracy also depend on which processing method was used, as some of the processing methods reduced or removed biases in the atmosphere or camera radiance.

Table 6-4. Uncertainty sources in the ICI3 modeling

Parameter	Symbol	Value	Source
Camera $RMSE_c$ $W[n]$ in equation 6 - 1			
NER	σ_{NER}	0.016 W/m^2sr	Detector noise, measured
Flat Field Correction	σ_{FFC}	0.137 $W/(m^2sr)$	Changes in the scene, measured
Extrapolation	σ_e	Modeled	Blackbody temperature range
Bandwidth	σ_b	Modeled	Uncertainty in camera spectral response
Radiometric Spatial	σ_s	0.067 W/m^2sr (min)	changes with scene and FPA-temperature
Radiometric Temporal	σ_t	0.27 W/m^2sr	measured
Atmosphere $RMSE_a$ $X[n]$ in equation 6 - 3			
Surface Temperature	σ_K	Modeled	Uncertainty in the MET surface measurements
Precipitable Water	σ_{pwv}	Modeled	Uncertainty in the precipitable water vapor measurements
Pixel Zenith Angle	σ_{FOV}	1° (estimated)	Zenith misalignment, changes with maintenance and wind

The resulting uncertainties were associated with a level of residual radiance. Then through the direct function relating residual radiance (or cloud radiance) to optical depth, the uncertainties were associated with an equivalent cirrus cloud optical depth, leading to a minimum reliable cloud detection. This cloud detection was specified based on the assumption that the cloud was a cirrus cloud. This is a valid assumption since cirrus clouds have the lowest emission and are expected to be near the limits of detection, whereas non-cirrus clouds tend to be warmer and thick and thus have higher emission and are easily detected. In this function there is a best-fit line and an upper and lower range of OD that was produced. All three of these values were reported for each uncertainty-equivalent cloud. Figure 6-14 shows this direct optical depth retrieval based on the logarithm of the cloud residual radiance. Given the natural logarithm of the radiance uncertainty, the vertical dashed line at -3, the uncertainty equivalent cloud optical depth could be determined. The best fit cloud is given by the orange dashed line. The maximum cloud optical depth is given by the blue dashed line, and the minimum cloud optical depth is given by the blue dotted line.

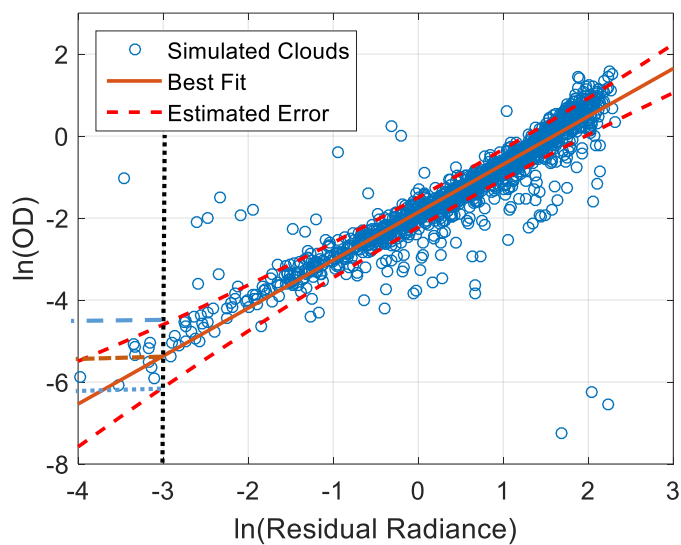


Figure 6-14. Direct optical depth retrieval based on the logarithm of the cloud residual radiance, showing the uncertainty-equivalent-cloud optical depth method, where the best-fit cloud was found by the best-fit line and the lower and upper range by the OD range estimate.

Noise-Equivalent Cloud Optical Depth

Similar to the metrics of NETD and NER, the noise in the system can be converted into an equivalent cirrus cloud. To do this, the noise-equivalent radiance was used to derive the cloud optical depth that would produce a SNR of 1. Table 6-5 shows the calculated noise-equivalent cirrus (NEC) cloud optical depth for two different noise levels experienced during the standard 15-frame averaging and single-frame acquisition with no averaging.

Table 6-5. Noise-equivalent cirrus cloud OD for 15 frame and single-frame acquisition

Averaging	NER	NEC lower range	NEC mean	NEC upper range
15 Frames	16.1 mW/(m ² sr)	4.2584e-04	0.0013	0.0037
None	47.3 mW/(m ² sr)	0.0020	0.0044	0.0095

These are very thin cirrus clouds, well below the visual limit for trained human observers between 0.03 and 0.06 (Sassen et al. 1988; Platt et al. 1987; Sassen & Cho 1992). These signals are likely below the observable limit in single thermal images, as well. Given a single frame, no person or algorithm could reliably detect these clouds. However, the signals from these clouds are present in the images, and a human observing a sequence of images may be able to detect the motion of these clouds over multiple frames. Frame-to-frame differencing, as employed by the SVM cloud processor described in chapter 5, may be able to detect these clouds by detecting changing or non-changing regions of the image.

Minimum Detectable Cloud

The limit for detectability in these imagers in a more practical sense is based on the noise combined with the FFC uncertainty. Since the scene impacts the camera response between FFC periods, no cloud detection method can reliably detect a cloud with a lower signal based on a radiance threshold. Using the 15-frame averaged NER of 16.1 mW/(m² sr) and the σ_{FFC} of 0.137 W/(m² sr), there is a minimum uncertainty in the ICI3 of 0.1374 W/(m² sr), Table 6-6 describes this uncertainty equivalent cloud (UEC) with radiance equal to this uncertainty (SNR = 1), which is at the threshold of detectability, and a more readily detectable cloud for which SNR = 5. The thicker cloud is the minimum cloud that can be reliably detected with a 99% probability of detection and less than 1% false positives on the clear sky. This is in the situation where the calibration accuracy and atmosphere simulation are perfect and there are no additional sources of uncertainty in the system. This is not a mode in which the ICI3 can operate.

Table 6-6. ICI3 minimum uncertainty equivalent cirrus cloud

SNR	Cloud Radiance	UEC lower range	UEC mean	UEC upper range
SNR = 1	0.1374 W/m ² sr	0.0086	0.0150	0.0262
SNR = 5	0.6870 W/m ² sr	0.0661	0.0964	0.1405

Algorithm 1 Direct Cloud Detection

To understand the specifics of the ICI3 cloud detection accuracy, the error analysis needs to be specific to each data processing routine. This section describes an analysis of the uncertainty in the direct cloud detection processing algorithm. This analysis made the assumption that all long-term camera errors caused by water spots on the lens, dust buildup, and camera drift were removed by calibrating with the onboard blackbody. In this situation, the radiometric accuracy was defined to be the same as in the laboratory calibration procedure. This analysis required a series of assumptions to be made about the scene and the camera, as summarized in Table 6-7.

Table 6-7. ICI3 camera and scene assumptions

Parameter	Value
Camera FPA-Temperature	20 °C
FPA-Temperature Rate of Change	0 °C/min
Scene Radiance	6 W/(m ² sr)

When combining all the sources of radiometric uncertainty, calibration, extrapolation, bandwidth, FFC, and noise with the atmosphere uncertainties, the resulting total system uncertainty was calculated. The resulting system uncertainty for three different regions in the field of view are shown in Table 6-8. The radiometric uncertainty in the ICI3 increases with zenith angle and thus this must be considered in the analysis. It has been selected to limit this analysis to a maximum uncertainty at 40° and use this

uncertainty in the detection analysis. The region out to 40° encompasses 82.8% of the ICI3 field of view.

Table 6-8. System uncertainty

Zenith	FOV-Average	40°
$0.47 \text{ W}/(\text{m}^2 \text{ sr})$	$0.47 \text{ W}/(\text{m}^2 \text{ sr})$	$0.48 \text{ W}/(\text{m}^2 \text{ sr})$

To minimize Type1 errors, clear sky falsely identified as clouds, the minimum detection threshold was an SNR of 2.5, or $1.21 \text{ W}/(\text{m}^2 \text{ sr})$. Using this threshold, the probability of a Type1 error was less than 1%; likewise, the probability of a Type2 error for a cloud with an SNR of 5 was less than 1%, leading to a detection probability of 99%. Clouds with a lower SNR have a lower probability of detection. Clouds with different SNRs, associated optical depths, and detection probabilities are summarized in Table 6-9. Using this algorithm, the cirrus cloud with a consistent 99% detection was relatively thick with an OD of 0.58. To a human observer it would be easily visible, and appear slightly blue. Clouds at visual limit near an OD of 0.06 are detected at a 7% probability.

These uncertainties can be applied to the cloud OD classification threshold to determine the cloud classification capability of the ICI3. The result of this process is shown in Table 6-10, where the system uncertainty is compared to the classification levels and a probability of detection and classification is determined. This suggests that the minimum classification threshold that should be used for the ICI3 direct cloud detection algorithm is a class of <0.5 , or level 4. Other thinner clouds are detected by the imager, but cannot be reliably distinguished from these thicker clouds.

Table 6-9. Cloud detectability for the direct cloud detection algorithm

SNR = 1, $L_{rr} = 0.48 \text{ W}/(\text{m}^2 \text{ sr})$, 7% Detectable Cloud			
	Zenith OD	Average OD	40° OD
Low	0.040	0.041	0.042
Best	0.060	0.061	0.063
High	0.091	0.091	0.094

SNR = 3, $L_{rr} = 1.54 \text{ W}/(\text{m}^2 \text{ sr})$, 69% Detectable Cloud			
	Zenith OD	Average OD	40° OD
Low	0.15	0.15	0.165
Best	0.22	0.22	0.22
High	0.31	0.31	0.32

SNR = 5, $L_{rr} = 2.42 \text{ W}/(\text{m}^2 \text{ sr})$, 99% Detectable			
	Zenith OD	Average OD	40° OD
Low	0.27	0.27	0.28
Best	0.39	0.39	0.40
High	0.56	0.56	0.58

Table 6-10. Calculated threshold levels for the ICI3 compared to the system uncertainty

Lev	OD	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
1	< 0.06	0.07	0.08	0.07	0.07	0.08	0.07	0.08	0.03	0.08	0.07	0.03	0.02
2	< 0.15	0.95	1.00	0.97	1.02	1.03	0.96	0.99	0.99	1.02	0.93	0.86	0.90
3	< 0.25	1.46	1.52	1.49	1.56	1.57	1.53	1.59	1.60	1.58	1.47	1.41	1.49
4	< 0.5	2.83	2.96	2.93	3.03	3.08	2.83	2.91	2.99	3.05	2.79	2.55	2.71
5	< 1	4.48	4.71	4.60	4.77	4.88	4.64	4.72	4.81	4.82	4.46	4.20	4.47
6	< 2	6.56	6.82	6.71	6.91	7.07	7.57	7.78	7.54	7.22	6.73	6.32	6.63
7	< 3	7.23	8.51	7.36	7.81	8.09	11.21	11.27	10.87	9.93	9.37	9.08	7.41
8	> 3												

	Below System Uncertainty
	~30% Probability of Detection
	~70% Detection Probability
	99% or Greater Detection and Classification Probability

Adaptive Cloud Detection Algorithms

The two adaptive processing algorithms are intended to reduce the uncertainty in the cloud detection by independently locating clear sky within the sky images and using these measurements to update the atmosphere model to produce a more accuracy residual radiance, L_{rr} .

In a best case, both the Adaptive Gradient and Time algorithm and the SVM algorithm remove all non-spatial biases in L_{rr} . The following analysis of detection accuracy was based on this best case. When this is the case, the remaining uncertainties in the radiometric calibration are the noise equivalent radiance σ_{NER} , the inter-FFC radiance change σ_{FCC} , and the spatial variation in the radiometric calibration σ_s . In the atmospheric correction, the variations in the surface-temperature-dependent σ_K and precipitable-water-vapor-dependent uncertainties $\sigma_{p_{wv}}$ will remain, as will the uncertainty due to the instrument alignment σ_{FOV} . These remain because both of the adaptive algorithms are dependent on the zenith angle of each pixel. The combined system uncertainty for this situation is shown in Table 6-11.

Table 6-11. System uncertainty for the adaptive cloud detection algorithms

Zenith	Average	40°
0.15 W/(m ² sr)	0.16 W/(m ² sr)	0.19 W/(m ² sr)

In this case, the uncertainty in the system was reduced by more than 50%. A similar reduction was observed in the minimum cloud detection threshold. Using the process of less than 1% probability of a Type1 error and a SNR = 2.5, a residual radiance of 0.48 W/(m² sr) can now be used as the minimum cloud detection threshold. Using this

threshold, the different cloud detection probabilities and associated OD are shown in Table 6-12.

As was done with the Direct cloud detection algorithm, these uncertainties were applied to the cloud OD classification thresholds to determine the cloud classification capability. The result of this process with the Adaptive Algorithms is shown in Table 6-13. These data show a minimum cloud classification level of <0.15 , or level 2 clouds. However, the level 1 clouds are below the system uncertainty, and the ICI3 will only detect these clouds at a probability of 6%. When they are detected, they will be classified as level 2 clouds.

Table 6-12. Cloud detectability for the adaptive cloud detection algorithms

SNR = 1, $L_{rr} = 0.19 \text{ W/(m}^2 \text{ sr)}$, 7% Detectable Cloud			
	Zenith OD	Average OD	40° OD
Low	0.001	0.011	0.014
Best	0.017	0.018	0.022
High	0.029	0.031	0.037
SNR = 3, $L_{rr} = 0.57 \text{ W/(m}^2 \text{ sr)}$, 69% Detectable Cloud			
	Zenith OD	Average OD	40° OD
Low	0.041	0.043	0.054
Best	0.061	0.064	0.080
High	0.091	0.095	0.130
SNR = 5, $L_{rr} = 0.95 \text{ W/(m}^2 \text{ sr)}$, 99% Detectable			
	Zenith OD	Average OD	40° OD
Low	0.076	0.080	0.10
Best	0.11	0.12	0.14
High	0.16	0.17	0.21

Table 6-13. Calculated threshold compared to the uncertainty of the adaptive algorithms.

Lev	OD	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
1	< 0.06	0.07	0.08	0.07	0.07	0.08	0.07	0.08	0.03	0.08	0.07	0.03	0.02
2	< 0.15	0.95	1.00	0.97	1.02	1.03	0.96	0.99	0.99	1.02	0.93	0.86	0.90
3	< 0.25	1.46	1.52	1.49	1.56	1.57	1.53	1.59	1.60	1.58	1.47	1.41	1.49
4	< 0.5	2.83	2.96	2.93	3.03	3.08	2.83	2.91	2.99	3.05	2.79	2.55	2.71
5	< 1	4.48	4.71	4.60	4.77	4.88	4.64	4.72	4.81	4.82	4.46	4.20	4.47
6	< 2	6.56	6.82	6.71	6.91	7.07	7.57	7.78	7.54	7.22	6.73	6.32	6.63
7	< 3	7.23	8.51	7.36	7.81	8.09	11.21	11.27	10.87	9.93	9.37	9.08	7.41
8	> 3												
		Below System Uncertainty											
		99% or Greater Detection and Classification Probability											

In this case, the cloud that will be detected and classified with a consistent 99% accuracy is a thin cirrus cloud with a maximum OD of 0.21 and a minimum OD of 0.1, at or below the limit of detection for trained visual observers. This is a much better situation for cloud detection, and suggests that the adaptive cloud algorithms should have much better performance for thin cloud detection. The performance of these algorithms in comparison with other co-located instruments are addressed in Chapter 7. This analysis includes data sets where the calibration of the cloud imager has been purposely compromised to explore the ability of these adaptive algorithms to correctly reduce system uncertainty.

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RESULTS OF THE BARROW DEPLOYMENT

Deployment of the ICI at ARM NSA

The two-year deployment of the ICI3 at the Barrow, AK Atmospheric Radiation Measurement (ARM) program North Slope of Alaska (NSA) site provided a unique opportunity to study LWIR cloud imager performance over extended deployments. At NSA the ICI3 was co-located with a variety of other well-characterized cloud measurement instruments, including imagers, LIDARs, radiometers, spectro-radiometers, and RADARs. Typically, many of these instruments are combined to create the ARM Active Remote Sensing of Clouds (ARSCL) value added product (VAP) (Clothiaux et al. 2001). However, during the 2012-2014 deployment of the ICI3, the cloud RADARs did not operate with a reliable calibration, preventing ARSCL data from being calculated. Therefore, alternative methods of understanding the ICI3 long-term performance had to be implemented. This chapter presents the results of that process. First, the operation of the ICI3 is presented. This includes changes in instrument calibration observed during the deployment. Then ICI3 data are compared with the AERI spectro-radiometer data integrated across the ICI3 spectral response function that was described in Chapter 4. This has provided a radiometric accuracy assessment of the ICI3, and has shown how the radiometric accuracy changed over the two-year deployment.

The ICI3 data also have been compared directly to the cloud fraction sensed by the co-located instruments that operated reliably during the ICI deployment. Inter-comparisons between the clouds sensed by each of these instruments were compared to

the different cloud processing techniques implemented on the ICI3. This allowed a comparison of the consistency of the different ICI data processing techniques, including the adaptive techniques when applied to ICI3 data with known radiometric biases.

These comparisons provide the best possible analysis of the ICI data operation during the ARM NSA deployment. Although they do not compare with the best cloud data products produced by the ARM, they do provide the best comparison that was available during the two-year deployment. Future deployments may be able to implement a more rigorous data analysis with the ARSCL VAP data.

Blackbody Calibration Analysis

The on-board blackbody calibration source was added to the ICI3 to both update the calibration in real-time and allow the calibration of the ICI3 to be tracked over time. A second, nearly-identical, blackbody source was kept in a laboratory during the duration of the ARM NSA deployment. It was intended that this second blackbody source would allow us to identify the nature of any observed changes in radiometry, with the options being the camera, the blackbody, or both. The environment of the ARM NSA site prevented this comparison from taking place.

When the ICI3 returned from ARM NSA, the cable that connected the blackbody had been severely corroded at the end that plugged into the ICI3 enclosure. The blackbody showed no signs of performance changes that would be caused by such corrosion, and similar corrosion was not observed on the ICI3 receptacle. It was therefore

assumed that this corrosion took place post deployment. The likely source was contamination of the plug by salt water when the ICI3 was packed for return to MSU.

This damage prevented direct comparison of the two blackbodies. Instead, the changes in system radiometry experienced during the deployment were studied using blackbody measurements from the first and last weeks of the deployment to derive two radiometric calibrations. These calibration differences were compared with the differences observed in the camera calibrations from before the deployment (the 2012 calibration) and from the calibration performed after the instrument returned to MSU (the 2016 calibration). The percent change in radiometric calibration offset and gain from the during-deployment tests is shown in Figure 7-1. Figure 7-2 shows the percent change in gain and offset between the pre-deployment and post deployment calibrations. The differences in these calibrations is summarized in Table 7-1.

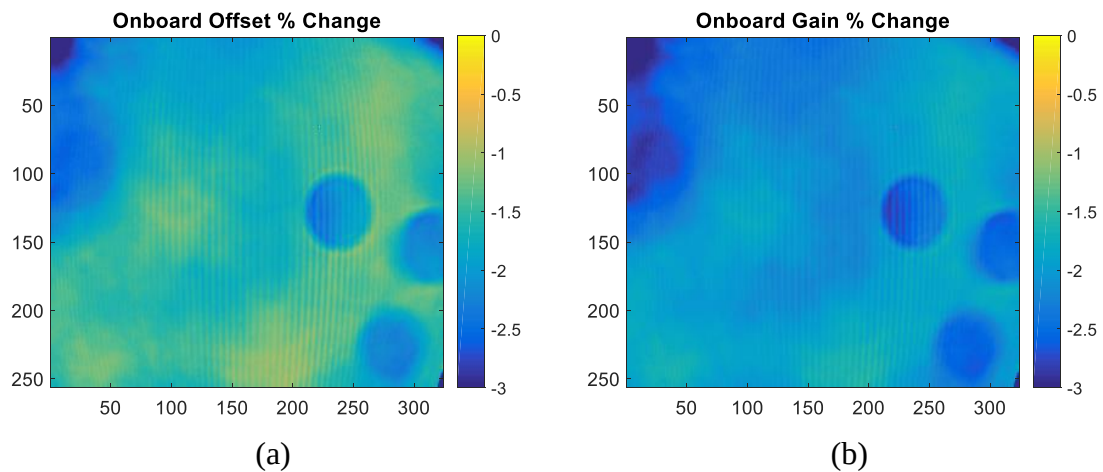


Figure 7-1. The percent change in gain and offset between the during-deployment first week calibration and during-deployment last week.

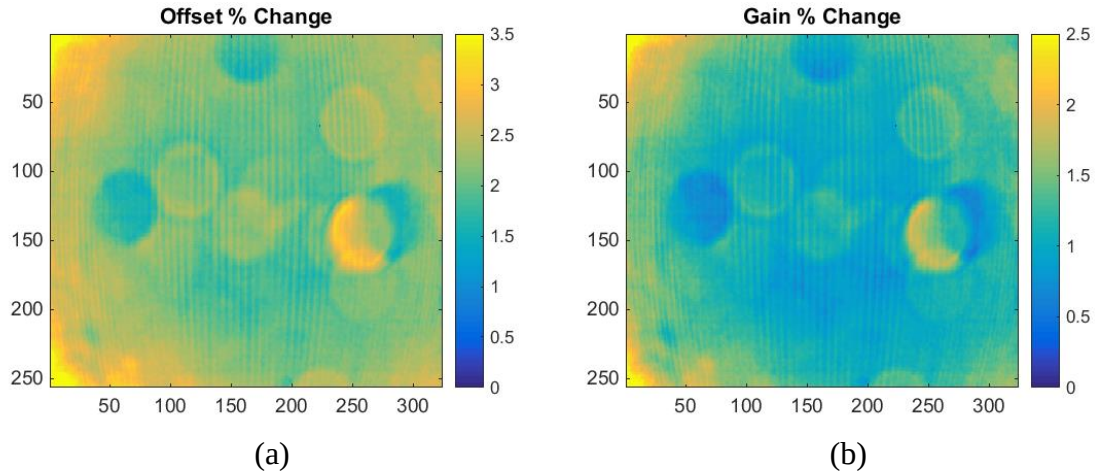


Figure 7-2. The percent change in gain and offset between the pre-deployment calibration and post deployment calibration. Water droplets on the lens can be seen to have left a permanent mark even after the lens was cleaned.

Table 7-1. Differences in the radiometric calibration sets

Calibration pair	Mean gain difference	Mean offset difference	Radiance difference in cold skies
Laboratory	1.2%	2.2%	-2.3 W/(m ² sr)
During deployment	-1.6%	2.1%	-3.6 W/(m ² sr)

The changes in gain and offset between the first and last weeks of deployment are similar in magnitude, but opposite in sign, to those derived in the laboratory before and after deployment. It is clear that the radiometric calibration of the camera changed during the deployment. What is not clear is if the blackbody changed. The fact that the sign of the derived gain and offset changes was different from the during-deployment and laboratory changes does support the conclusion that the blackbody did change.

The changes in the camera could be attributed to changes in the lens AR coating due to the damp salty environment and the repeated cleaning it underwent during deployment. This is supported by the prevalence of water droplets in the calibration differences, even in the laboratory calibrations where the camera lens was carefully

cleaned before each test. This could be partly mitigated by using a lens with a hard carbon front surface. This would reduce the transmission of the lens by 5 to 10%, but it would reduce changes to the lens over time.

Comparisons with the AERI

At ARM NSA co-located with the ICI3 during its two-year deployment was an atmospheric emitted radiance interferometer (AERI). The AERI is a ground-based spectro-radiometer that observed the down-welling infrared spectral radiance from the zenith atmosphere [4], [5]. Figure 7-3 shows an image of an AERI similar to the one deployed at ARM NSA.



Figure 7-3. The Atmospheric Emitted Radiance Interferometer at the ARM Southern Great Plains Site; the ARM NSA site has a similar instrument. (Photo from arm.gov).

The AERI outputs radiometrically calibrated spectral radiance from $3.3\text{ }\mu\text{m}$ to $25.0\text{ }\mu\text{m}$. This region encompasses the $5\text{ }\mu\text{m}$ to $20\text{ }\mu\text{m}$ spectral response of the ICI3.

Therefore, by integrating the AERI spectral radiance data over the same spectral response as the ICI3, an assessment of the ICI3 radiometric accuracy was made.

AERI Integrated Radiance

The AERI data from 1 January 2012 through 31 December 2014 was downloaded from the ARM archive for both channel 1 (Gero et al. 2015a) and channel 2 (Gero et al. 2015b) of the instrument. These data contain both the spectral radiance from the AERI and the variance in the spectral radiance based on a calibration analysis of the instrument (Demirgian & Dedecker 2005). By integrating across the ICI3 spectral response, a radiance was calculated that was compared to the ICI3 calibrated radiance at the zenith. By similarly integrating across the variance in the spectral radiance, an estimate of the AERI uncertainty for a particular measurement was determined. This value was near 0.01 W/(m²sr) for all measurements.

Uncertainty in the Spectral Response Function The spectral response function of the ICI3 is not known precisely and this causes an uncertainty in the spectral integration of the AERI data. The spectral response function also ties in to the calibration of the ICI3 and therefore the differences between integrated radiances from different spectral response overestimates the error caused by the ICI3 spectral response uncertainty. Approximating this uncertainty is a multi-step process. First, a camera gain and offset calibration was derived using each of the spectral responses derived by the genetic algorithm and the average spectral response (used to calibrate the data during processing). Next, AERI data were integrated over each of these ICI3 spectral responses,

resulting in an associated set of integrated radiances. These integrated radiances for each response were then converted to a simulated Photon camera digital number using the gain and offset for the particular spectral response. Then these digital numbers were converted back into radiances using the average or best-estimate spectral response. The difference between the integrated radiance from the best-estimate response and all other responses was the error in the measurement of that particular spectral response relative to the correct response for the ICI3. The resulting radiance differences had a standard deviation of $1.01 \text{ W}/(\text{m}^2 \text{ sr})$ and a mean of $-0.54 \text{ W}/(\text{m}^2 \text{ sr})$. A sample of these differences is shown in Figure 7-4.

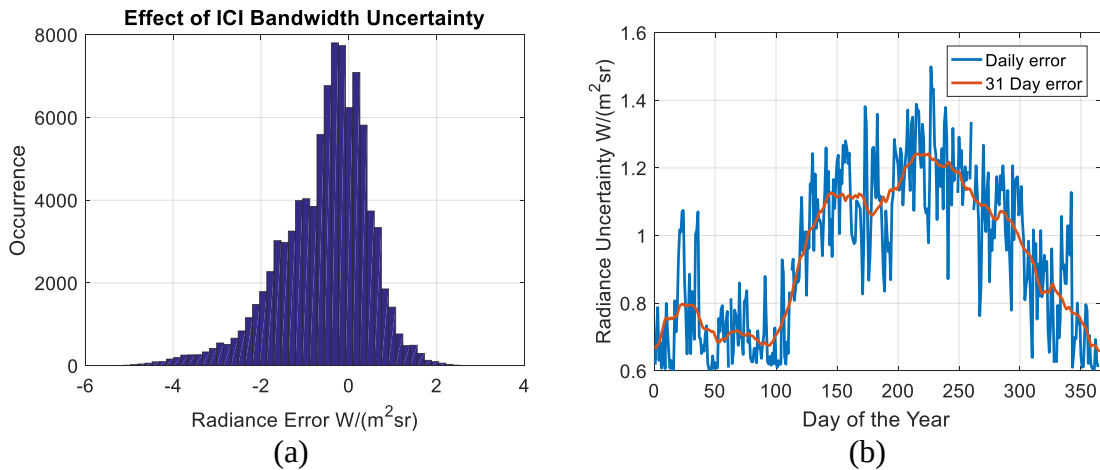


Figure 7-4. The differences in the AERI integrated radiances using the different spectral responses estimated by the genetic algorithm for the ICI3.

Uncertainty in the ICI Zenith Radiance The final source of uncertainty in the comparison is the uncertainty in the ICI3 zenith data. This uncertainty is both in the radiometric accuracy of the data and the alignment of the ICI3 to the AERI. To reduce the alignment uncertainty, a 15-minute averaging was applied to the AERI data and the ICI data within 5 degrees of the zenith. This averaging time has been shown to be

sufficient to produce an angle-independent cloud measurement (Kassianov 2005). For this comparison, the ICI3 radiometric uncertainty was estimated as the combination of the temporal radiometric accuracy $\sigma_t = 0.27 \text{ W}/(\text{m}^2 \text{ sr})$, the average spatial radiometric accuracy $\sigma_s = 0.067 \text{ W}/(\text{m}^2 \text{ sr})$, the FFC correction random bias $\sigma_{FFC} = 0.137 \text{ W}/(\text{m}^2 \text{ sr})$, and the noise-equivalent radiance $\sigma_{NER} = 0.016 \text{ W}/(\text{m}^2 \text{ sr})$. This resulted in an estimated average ICI uncertainty of $0.31 \text{ W}/(\text{m}^2 \text{ sr})$.

Results of the AERI Comparison

The combination of the two radiometric camera calibrations and the use of the on-board blackbody during deployment led to four different calibrations for the ICI3. These calibrations are as follows: 1) the pre-deployment derived laboratory calibration, referred to as the Standard 2012 Calibration (2012S); 2) the 2012S calibration continually adjusted with the on-board blackbody, or the 2012 Blackbody-Adjusted calibration (2012BB); 3) the post-deployment laboratory calibration, referred to as the Standard 2016 Calibration (2016S); and 4) the 2016S calibration adjusted with the blackbody (2016BB). Each of these calibrations has been compared to the AERI. A fifth, purposely biased, calibration also was used on the ICI3 to determine the effectiveness of the adaptive processing routines. This calibration used an incorrect spectral response that was a combination of spectral response 1 and spectral response 5 of the responses derived using the FTIR systems, as described in Chapter 5. This spectral response function gave the best performance before the implementation of the genetic algorithm, and will be referred to as Band51.

To get a good comparison, careful data processing of the ICI3 and the AERI had to be implemented. Only the ICI3 data within 5 degrees of the zenith were used. Instances where the AERI hatch, or the ICI3 hatch did not properly open had to be removed from these data. The data also were temporally aligned by optimizing the correlation between the ICI and AERI data. This led to a shift in the ICI3 data by -210 seconds. This difference could be caused by errors in the instrument clocks, or by pointing errors between the ICI and the AERI. Initial comparisons showed that all 5 possible spectral response models followed the same trends as the integrated AERI radiance. The comparison of the 2016S data and the AERI is shown in Figure 7-5. It is important to note there is a period from November 2012 through December 2012 where the AERI did not operate, and a similar period from July 2013 into August 2013 where the ICI3 did not operate.

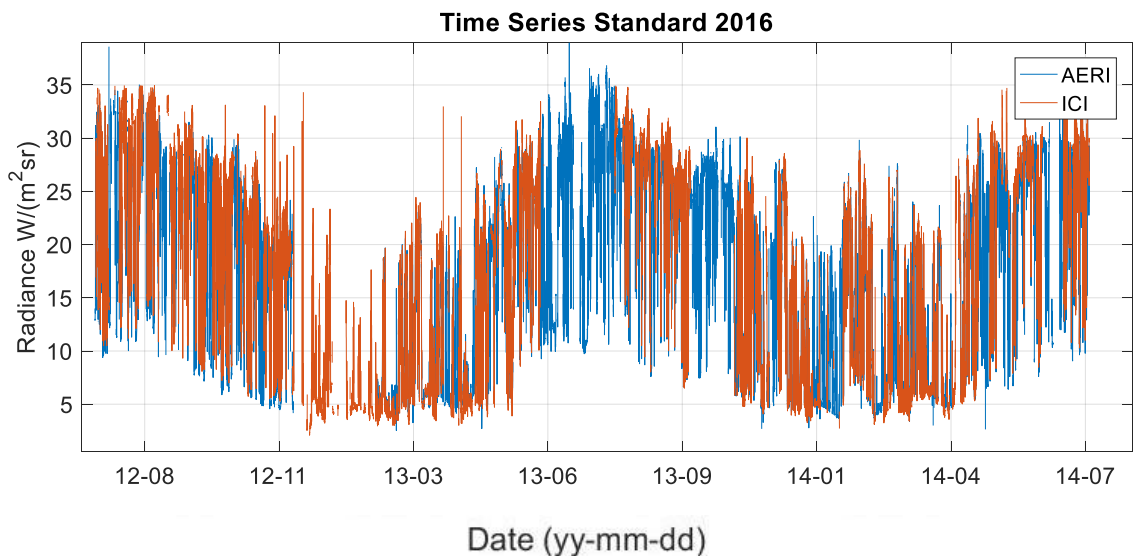


Figure 7-5. Data from the complete deployment of the ICI3 using the standard 2016 calibration with no adjustments from the ICI3 on-board blackbody.

From Figure 7-5 an annual cloud cycle can be seen. For any time period the minimum radiances are clear skies, and the maximum radiances overcast skies with low-thick clouds. Using these facts, it can be seen that during the winter some the instruments both measure very cold clear skies and near surface clouds with reduced temperature. The radiometrically cold winter skies are due to the very low precipitable water present in these atmospheres. The decreased thick cloud temperature is due to decreased air temperature.

Comparing the AERI and ICI3 agreement for each of the ICI3 calibrations shows the difference in the two laboratory calibrations did matter, and the camera did change during the deployment. It also demonstrated that the blackbody calibrations tended to improve the agreement between the ICI3 and the AERI throughout the deployment. In data from early in the ICI3 deployment, as shown in Figure 7-6, the 2012S and the two blackbody-adjusted calibrations compare well with the AERI data. However, a distinct offset is observed between the 2016S ICI3 calibration and the AERI data.

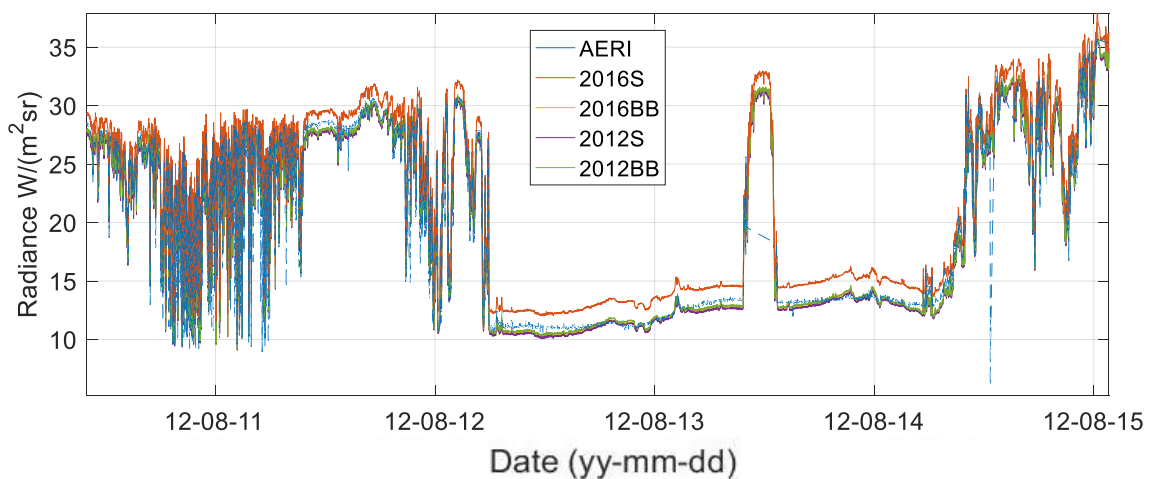


Figure 7-6. Data from early in the ICI3 deployment for all four data calibrations. The 2012S and the two blackbody-adjusted calibrations follow the AERI data best.

The agreement changed early in the deployment, as shown in Figure 7-7 for data from the middle deployment when the 2012S calibration no longer tracked the AERI, but the 2016S calibration and the two blackbody-adjusted calibrations did. This continued with data through the end of the, as shown in Figure 7-8.

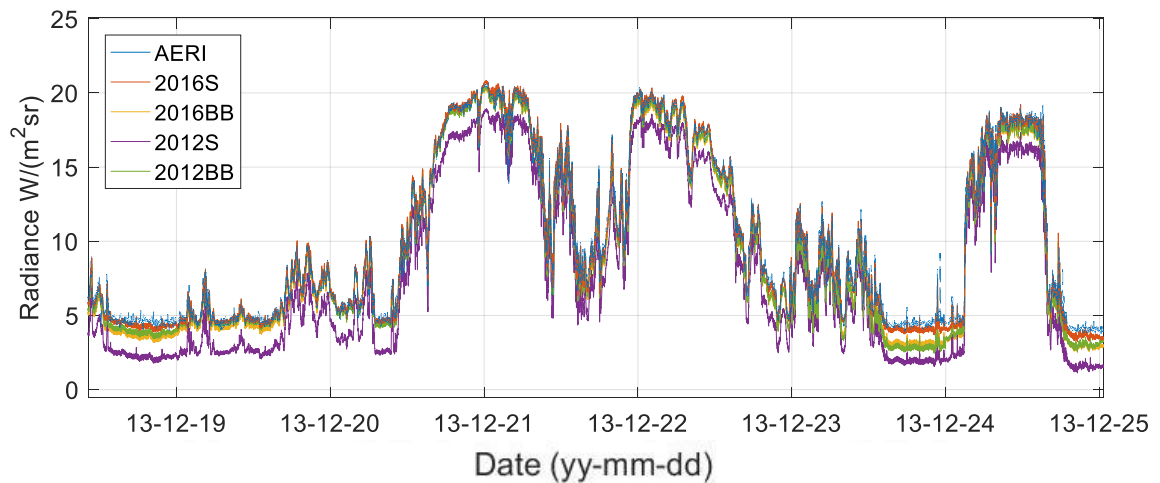


Figure 7-7. Data from the middle of the ICI3 deployment for all four data calibrations. At this point the 2012 standard calibration no longer tracked the AERI, but the 2016 standard calibration did. The two blackbody-adjusted calibrations also followed the AERI data.

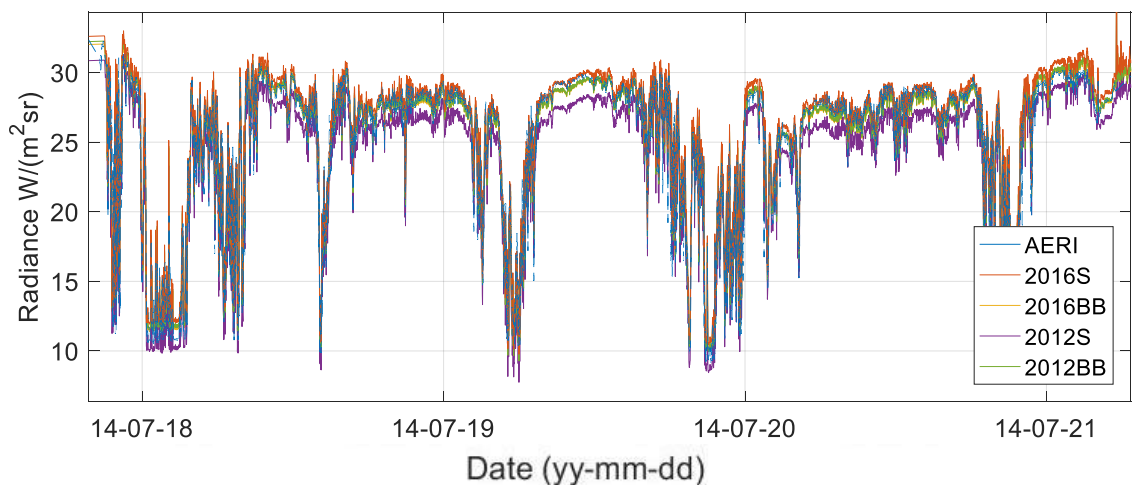


Figure 7-8. Data from near the end of the ICI3 deployment for all four data calibrations. The 2016 standard calibration and two blackbody adjusted calibrations tracked the AERI data at this time.

The 30-day-sliding-window average difference between the AERI and the ICI3 data are shown in Figure 7-9. This comparison uses both the 2016S and 2016BB calibrations and the average of these two calibrations. These data started with a large radiometric difference near $1 \text{ W}/(\text{m}^2 \text{ sr})$ at the beginning of the deployment. The difference quickly decreased as the 2016S and 2016BB calibrations converged after the 2012-2013 winter. The blackbody did not operate at the start of 2013 and all data are equal to 2016S. Throughout the deployment, the difference between the AERI and the ICI3 fell within the uncertainty defined by the ICI3 spectral response function uncertainty.

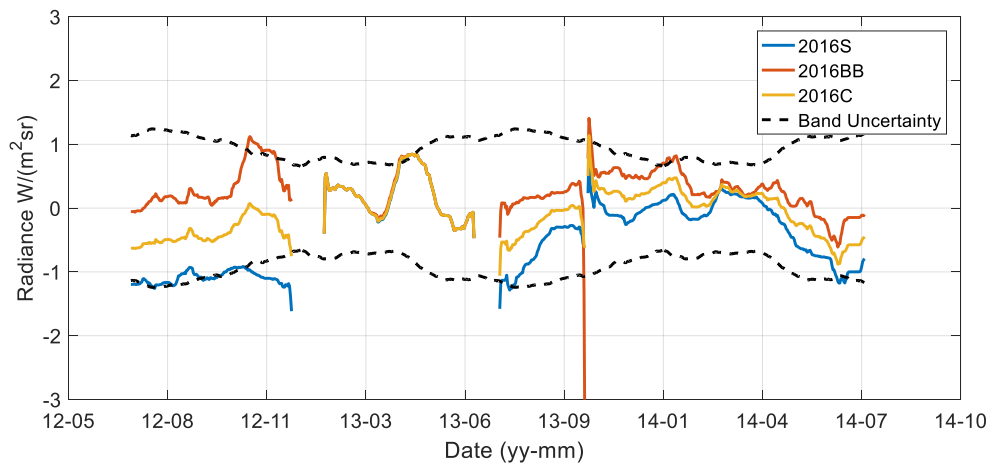


Figure 7-9. The difference between the AERI and the ICI3 data using both the 2016 standard and the 2016 blackbody-adjusted data. These data started with a wide difference, but quickly converged after the 2012-2013 winter. The blackbody did not operate at the start of 2013.

There are three clearly observable sudden changes in 2016S accuracy at the end of November 2012, in August 2013, and near October 2013. These are all times when the instrument was restarted after a period of not operating. One possible cause of these

errors is that at each of these times the lens was cleaned as part of the routine maintenance when restarting the system. This effect should be studied in future systems.

The difference between the AERI and the ICI3 using the 2012S and 2012BB calibrations is shown in Figure 7-10. For these data, the radiometric accuracy was opposite from before: the data start with a small difference, but the 2012S calibration had lower performance after the 2012-2013 winter. By the end of the deployment, these calibrations produced a difference that was similar to the differences experienced by the 2016S and 2016BB calibrations at the start of the deployment. The changes in calibration during periods of maintenance can be observed in the 2012 calibrations as well.

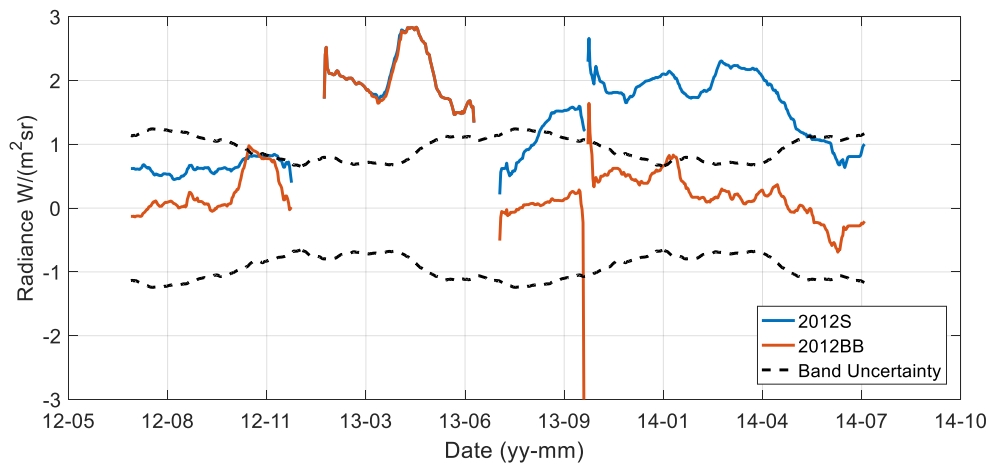


Figure 7-10. The difference between the AERI and the ICI3 data using both the 2012 standard and the 2012 blackbody adjusted data. These data started with a small difference, but the 2012 standard calibration degraded during the 2012-2013 winter.

The lowest error on both the 2016BB and 2012BB data sets occurred at the start of the experiment through October 2012 and from August 2013 through September 2013. The blackbody surface was cleaned using compressed air to remove dust at the start of the deployment, then again during an intense maintenance period in August 2013. This

supports a hypothesis that the blackbody did degrade during the experiment, and these changes could be related to dust buildup.

The relationship between the AERI and the ICI3 during the entire deployment is shown as a scatter plot and a difference histogram for the 2016S data in Figure 7-14 and for the 2016BB data in Figure 7-15. For these plots, blackbody adjustment errors where the camera did not properly align to the blackbody have been removed.

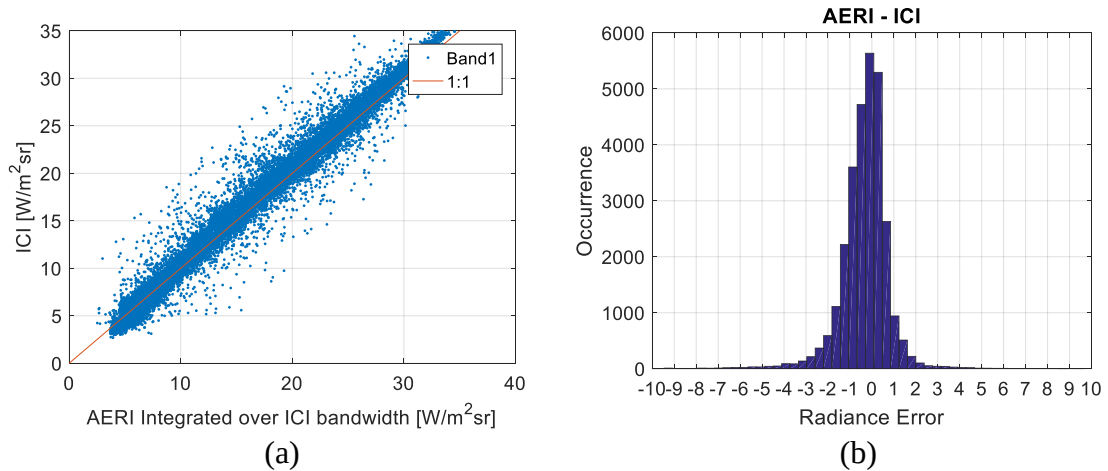


Figure 7-11. Scatter plot (a) and difference histogram (b) for the AERI and ICI3 data over the entire ARM NSA deployment using the 2016S ICI3 calibration.

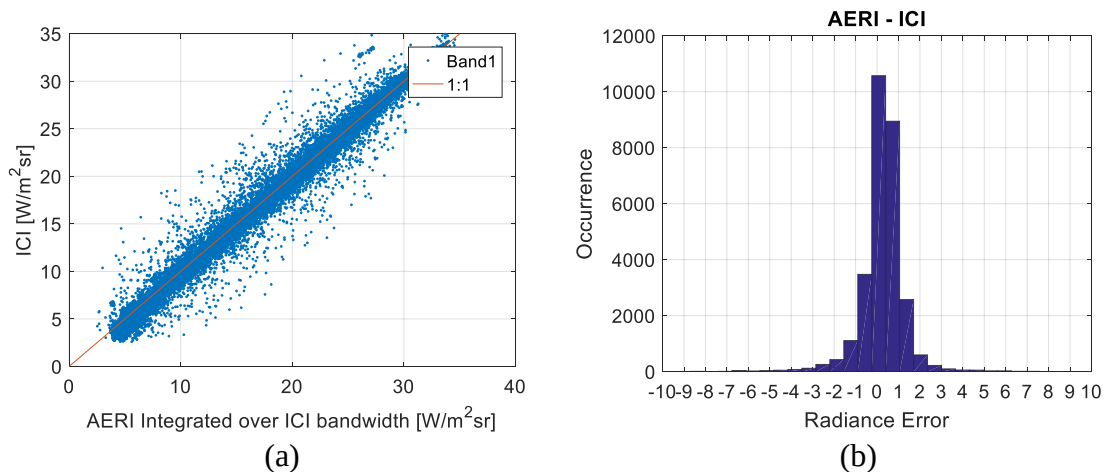


Figure 7-12. Scatter plot (a) and difference histogram (b) for the AERI and ICI3 data over the entire ARM NSA deployment using the 2016S ICI3 calibration.

In these figures the difference between the AERI and the ICI are nearly zero mean, and the ICI versus AERI data fall very close to a 1:1 line. In the scatter plot and difference histogram of the biased Band 51 data set shown in Figure 7-13, much of the data fall along a 1:1 line except at low radiance, where the relationship has a distinct curve. This also can be seen in the difference histogram as a nonzero mean.

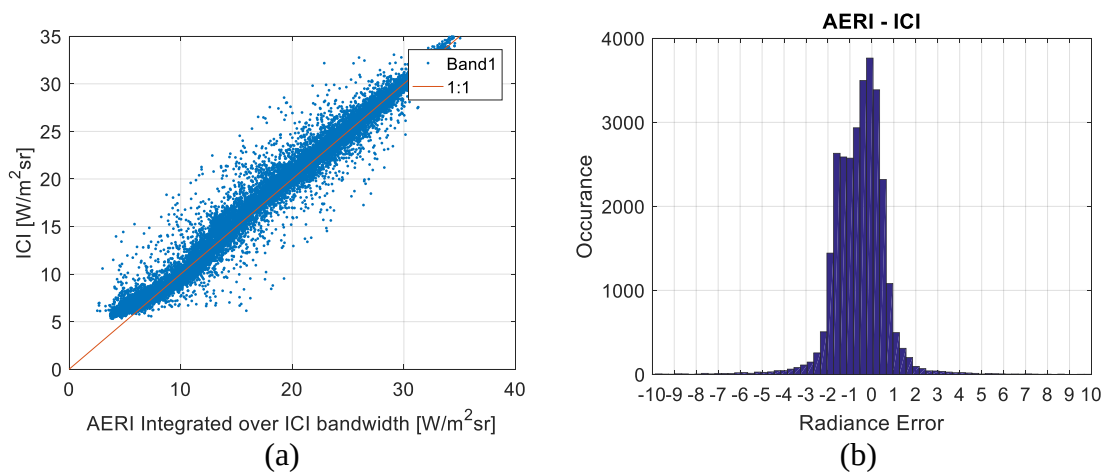


Figure 7-13. Scatter plot (a) and difference histogram (b) for the AERI and ICI3 data over the entire ARM NSA deployment when using the Band 51 calibration.

Table 7-2 through Table 7-6 summarize the differences experienced in each of the four good ICI3 calibrations and the biased Band51 calibration. In these data, the 2016S and 2016BB data have the lowest biases for scenes with radiances less than 15 W/(m² sr). These scenes would be clear skies and thin cirrus clouds. The Band 51 and 2012S calibrations experience the highest biases for these low radiance scenes, with Band 51 ICI3 data having significantly higher radiance than the AERI and 2012S data have lower radiance than the AERI. It is very interesting to note that the two blackbody-adjusted data sets do not always agree. It is believed these differences exist due to the different FPA-temperature compensation coefficients used in each of these calibrations.

Table 7-2. AERI - ICI3 differences using the 2016 standard calibration

Parameter	Mean	Standard Dev	Median
Difference	-0.32 W/(m ² sr)	1.14 W/(m ² sr)	-0.21 W/(m ² sr)
Difference $L_s < 15$ W/(m ² sr)	-0.11 W/(m ² sr)	1.19 W/(m ² sr)	0.09 W/(m ² sr)
Difference $L_s > 15$ W/(m ² sr)	-0.53 W/(m ² sr)	1.29 W/(m ² sr)	-0.50 W/(m ² sr)

Table 7-3. AERI - ICI3 differences using the 2016 blackbody adjusted calibration

Parameter	Mean	Standard Dev	Median
Difference	0.27 W/(m ² sr)	1.09 W/(m ² sr)	0.32 W/(m ² sr)
Difference $L_s < 15$ W/(m ² sr)	0.05 W/(m ² sr)	3.09 W/(m ² sr)	0.41 W/(m ² sr)
Difference $L_s > 15$ W/(m ² sr)	0.18 W/(m ² sr)	1.29 W/(m ² sr)	0.22 W/(m ² sr)

Table 7-4. AERI - ICI3 differences using the 2012 standard calibration

Parameter	Mean	Standard Dev	Median
Difference	1.58 W/(m ² sr)	1.19 W/(m ² sr)	1.68 W/(m ² sr)
Difference $L_s < 15$ W/(m ² sr)	1.87 W/(m ² sr)	1.27 W/(m ² sr)	2.06 W/(m ² sr)
Difference $L_s > 15$ W/(m ² sr)	1.30 W/(m ² sr)	1.32 W/(m ² sr)	1.33 W/(m ² sr)

Table 7-5. AERI - ICI3 differences using the 2012 blackbody adjusted calibration

Parameter	Mean	Standard Dev	Median
Difference	0.67 W/(m ² sr)	1.36 W/(m ² sr)	0.48 W/(m ² sr)
Difference $L_s < 15$ W/(m ² sr)	0.49 W/(m ² sr)	3.71 W/(m ² sr)	0.78 W/(m ² sr)
Difference $L_s > 15$ W/(m ² sr)	0.41 W/(m ² sr)	1.41 W/(m ² sr)	0.27 W/(m ² sr)

Table 7-6. AERI - ICI3 differences using the band 51 blackbody adjusted calibration

Parameter	Mean	Standard Dev	Median
Difference	-0.54 W/(m ² sr)	1.18 W/(m ² sr)	-0.47 W/(m ² sr)
Difference $L_s < 15$ W/(m ² sr)	-0.91 W/(m ² sr)	1.19 W/(m ² sr)	-1.01 W/(m ² sr)
Difference $L_s > 15$ W/(m ² sr)	-0.18 W/(m ² sr)	1.25 W/(m ² sr)	-0.12 W/(m ² sr)

In the two blackbody data sets there is an increased uncertainty for low-radiance scenes below 15 W/(m² sr). This poses a significant issue, as these are the thin-cloud scenes. The cause of this increased uncertainty is likely the extrapolation that is taking

place, coupled with emissivity uncertainties in the deployed blackbody. These uncertainties cause a noise in the slope and offset of the radiometric calibration to have a random change over time, which is most prominent in these cold scenes.

The 2016S calibration had a negative bias with the AERI, whereas the 2016BB adjusted calibration had a slightly positive bias relative to the AERI. This led to the idea that a combination of these two data sets may have the best performance. Figure 7-14 and Table 7-7 summarize such a data set, referred to as 2016Best. In these data, when a good blackbody reference was present the data are the average of 2016BB and 2016S, but when blackbody corrections were not present the 2016S data were used. The resulting data had a nearly zero mean bias for both low-radiance and higher-radiance scenes. However, there still was an increase in uncertainty in the low-radiance data.

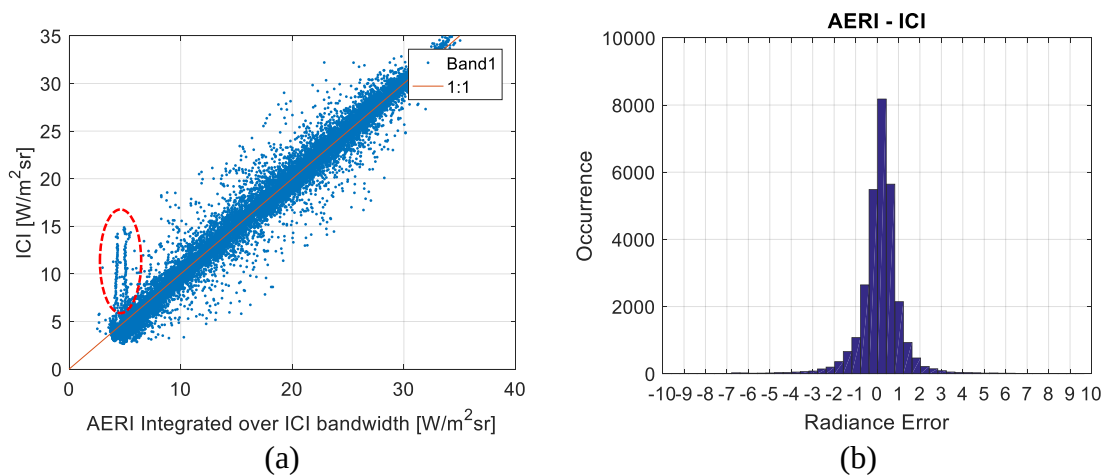


Figure 7-14. The 2016 Best Calibration scatter plot (a) and histogram (b). The region circled in red in panel (a) is 24 hours of bad data that occurred when the camera rotation mount locked up. These data were replaced with the 2016S data during instrument comparisons.

Table 7-7. AERI - ICI3 differences using a selective combination of the 2016 standard and blackbody adjusted calibrations

Parameter	Mean	Standard Dev	Median
Difference	0.09 W/(m ² sr)	1.14 W/(m ² sr)	0.14 W/(m ² sr)
Difference $L_s < 15$ W/(m ² sr)	0.05 W/(m ² sr)	1.87 W/(m ² sr)	0.30 W/(m ² sr)
Difference $L_s > 15$ W/(m ² sr)	0.00 W/(m ² sr)	1.29 W/(m ² sr)	-0.01 W/(m ² sr)

Overall, the consistency of the ICI3 with the AERI data gives us a strong sense of our radiometric accuracy of the instrument. Throughout the deployment, the ICI3 blackbody-adjusted data fell within the uncertainty in the ICI3 spectral responsivity. The improved accuracy of the blackbody-adjusted data following periods of blackbody cleaning does suggest that there was a systematic change in the blackbody, caused by a buildup of dust and possibly other contaminants on the blackbody surface. However, an absolute instrument accuracy and blackbody performance could not be determined.

Cloud Data Measured with the ICI3

The ICI3 cloud data provide a source of information about instrument performance that is used in this section to build an understanding of the performance of the ICI3 during the ARM NSA deployment. The error in the ICI3 residual radiance that is used for cloud detection is approximated. The cloud cover differences observed with the different calibration and processing methods are quantified.

Estimates of Uncertainty in the ICI3 Data

It was difficult to directly determine when an error occurred in the ICI residual radiance values (recall, “residual radiance” refers to the radiance that remained after estimated clear-sky emission was removed from the measurements). However, when ICI3

gave residual radiance values less than 0 W/(m² sr), these values were obviously in error. This led to a best-case approximation of the ICI3 residual radiance error. From these estimates, the reliably detectable cloud optical depth was determined. This required the imager to have a zero mean bias with the residual radiance. Therefore, this process was only conducted on the three data sets that showed close-to-zero bias in comparisons with the AERI: the 2016S, 2016BB, and 2016Best data sets. To make this assessment, first the distribution of known error points with negative residual radiance was determined, then these points were mirrored across the zero point and a standard deviation was calculated. From this standard deviation, an uncertainty-equivalent cloud optical depth was determined using the process outlined in Chapter 6. Figure 7-15 shows the results of this process for the 2016BB calibration. Table 7-8 shows the estimates of these errors and their prevalence in the data for the 2016S, 2016BB, and 2016Best data sets. This analysis was restricted to the data within five degrees of the zenith (the same data used to compare with the AERI).

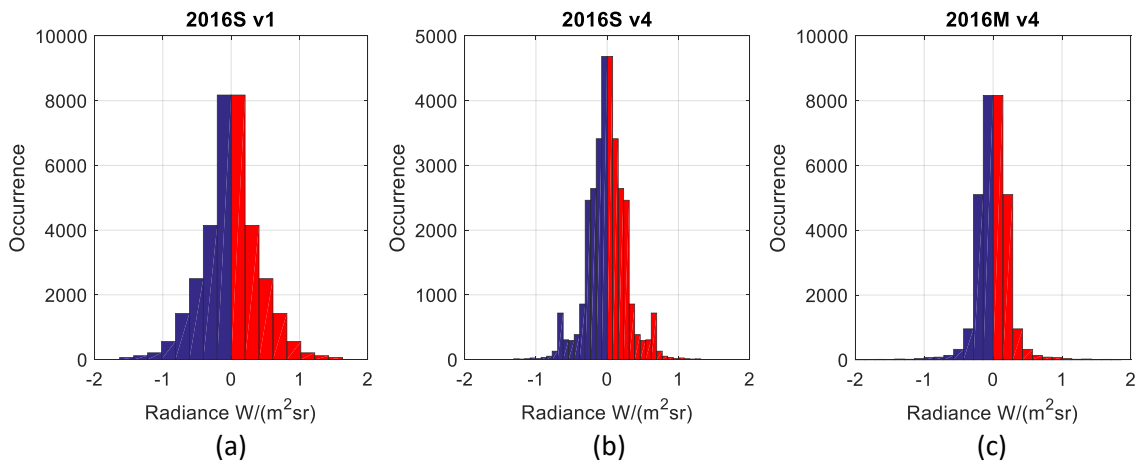


Figure 7-15. The negative residual radiance in blue, and its reflection across zero in red for two different processing methods: (a) direct physics, (b) gradient-and-time adaptive algorithm using a three-frame history.

Table 7-8. Calibration processing estimates

Data Set	Processing Method	Estimated Uncertainty	Error Rate	Zenith OD, SNR=5
2016S	V1	0.41 W/(m ² sr)	3.3%	0.49
2016S	V4 3 min	0.27 W/(m ² sr)	3.1%	0.30
2016S	V4 60 min	0.25 W/(m ² sr)	3.1%	0.28
2016BB	V1	0.67 W/(m ² sr)	7.5%	0.88
2016BB	V4 3 min	0.25 W/(m ² sr)	2.4%	0.28
2016BB	V4 60 min	0.47 W/(m ² sr)	1.0%	0.57
2016Best	V1	0.62 W/(m ² sr)	5.6%	0.80
2016Best	V4 3 min	0.25 W/(m ² sr)	2.2%	0.28
2016Best	V4 60 min	0.43 W/(m ² sr)	0.1%	0.52

Using either the 3-minute (or 3-frame) gradient and time-adaptive algorithms (referred to as version four or v4), or the 60-minute v4 algorithm reduces the number of frames where the ICI3 reports negative residual radiance. This adds support to the claim that these algorithms do reduce the uncertainty in the cloud data processing.

Comparisons Between Processing Routines

For the following data, a 36-hour period was selected because it presented highly variable cloud conditions and allowed for good comparisons between the data sets. In Figure 7-16, four different data processing routines are shown over this 36-hour period: the 2016S calibration and the Band 51 calibration, both with the direct processing (v1) and the adaptive v4 processing applied. The cloud fraction reported from both data sets using the v4 algorithm was nearly identical over this full period. This further demonstrates the ability of the adaptive calibration methods to correct for biases in the calibration or in the atmospheric model, both of which are present in the Band 51 data set.

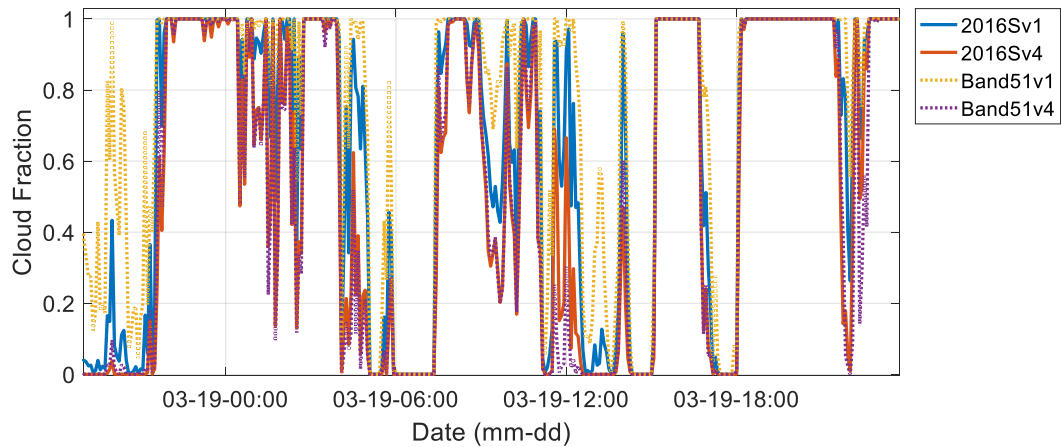


Figure 7-16. Time series of four different data processing routines over a 36-hour period selected for high variability. The figure shows the 2016S with the direct processing (v1) and the adaptive v4 processing along with two of the SVM outputs.

Observations of the same time period using the two SVM data sets showed interesting, but less than ideal, results. Using the current SVM algorithms, these routines showed similar trends, but did have distinct differences. SVM1 (trained to classify clear sky and thick clouds) underreported cloud amount during this period. SVM2 (trained to classify clear sky from all clouds) over reported clouds compared to the v1 and v4 processing methods. It is very important to note that both SVM cloud classifiers did show similar cloud fraction trends over time, and the current cloud fraction (v1 or v4) tended to always fall between these two results. This suggests that with fine tuning, the SVM algorithm could report a cloud amount consistent with the other methods. The SVM data processing all took place without any reliance on radiometric calibration of the instrument or on an atmospheric model.

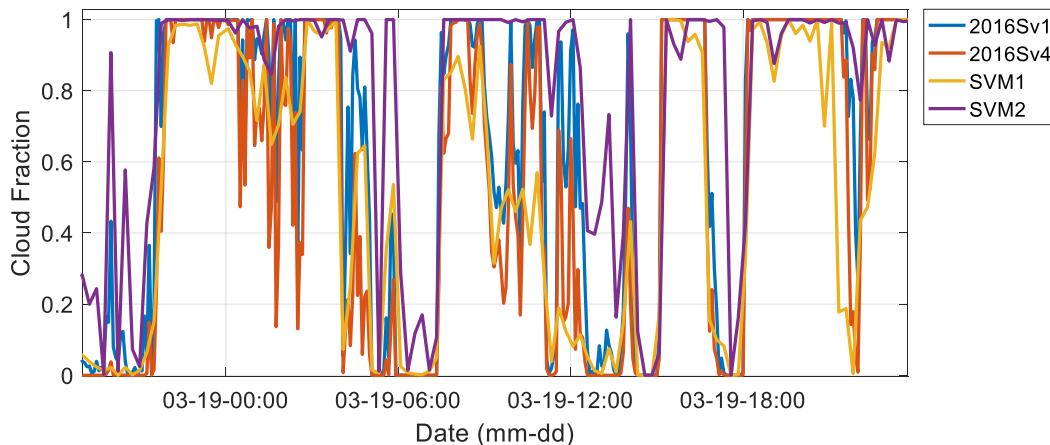


Figure 7-17. Time series of four different data processing routines over a 36-hour period selected for high variability. The figure shows the 2016S with the direct processing and the adaptive v4 processing along with two of the SVM outputs.

ICI-to-ARM Instrument Comparisons

During the deployment at ARM NSA, the ICI3 was deployed next to several other cloud-sensing instruments. This section provides a comparison of the ICI3 with the ARM cloud-sensing instruments that were operating during the July 2012 to August 2014 ICI operating period. Five co-located cloud sensing instruments produced a cloud fraction during the ICI3 deployment to Barrow AK. Three of these instruments were passive sensors. Example images of these passive sensors are shown in Figure 7-18. These passive sensors included: the Total Sky Imager (TSI, a visible wavelength cloud imager), the Multifilter Rotating Shadowband Radiometer (MFRSR, a visible and near infrared radiometer), and the Sky Radiometers for Downwelling Radiation (SKYRAD, a multi-wavelength hemispheric radiometer package). Two active LIDAR instruments were also located at ARM NSA, the Ceilometer (CEIL) and the Micro-Pulse Lidar (MPL). Example photos of these instruments are shown in Figure 7-19. The following sections provide

descriptions of these cloud instruments and where possible describes their operating specifications. Note that none of the instrument photos were taken at Barrow.

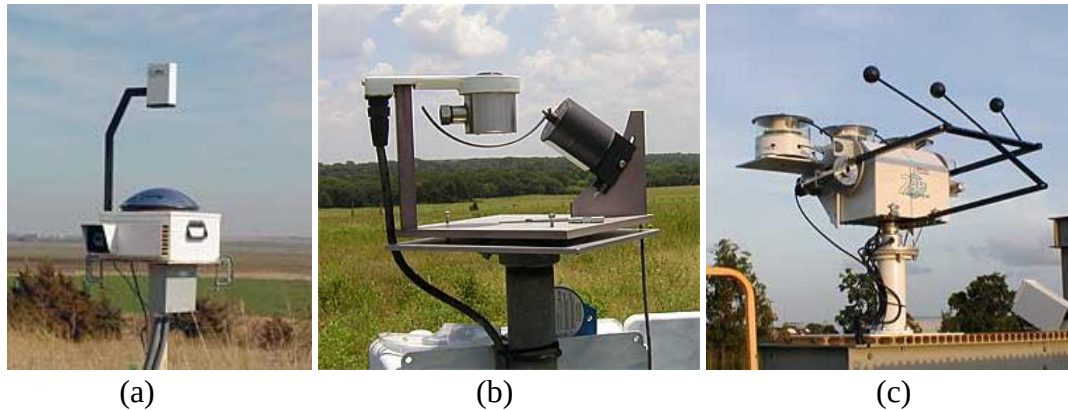


Figure 7-18. Example photos of the three passive instruments that were installed at the ARM NSA site (a) the TSI, (b) the MFRSR, and (c) the SKYRAD. These photos are of similar instruments located at ARM SGP (photos from arm.gov).

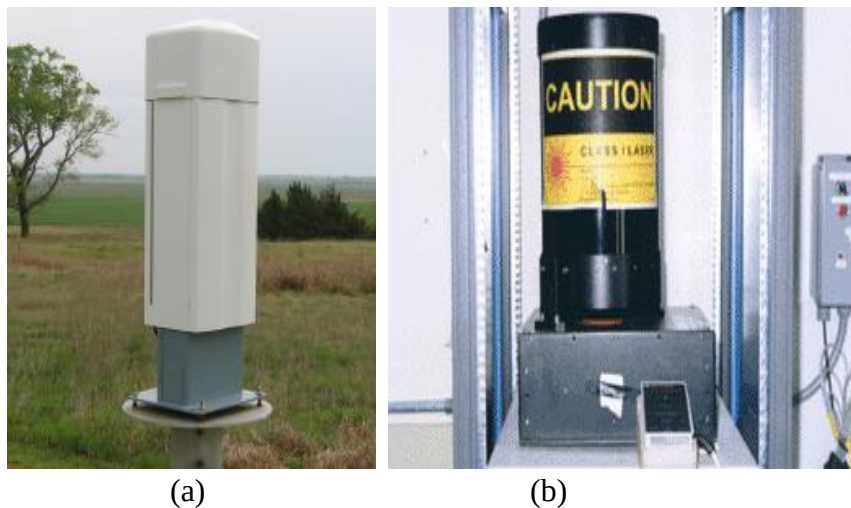


Figure 7-19. Example photos of the two active instruments that operated at the ARM NSA site during the ICI deployment (a) the CEIL and (b) the MPL, these photos are from similar instruments installed at ARM SGP (photo from arm.gov).

Total Sky Imager

The Total Sky Imager (TSI) is a visible-wavelength cloud imager that uses a reflective dome mirror and red-green-blue color camera to image the entire sky dome (Long et al. 2001). Figure 7-18 (a) shows a TSI instrument installed at ARM SGP. The TSI uses a red/blue cloud detection scheme that relies on illumination by sunlight. Dawn and dusk periods also cause problems due to the changes in colors at this time and the TSI is therefore limited to operate during daylight hours when the solar elevation is greater than 10 degrees (which excludes the winter season at the NSA site) (Long et al. 2001). The TSI data products of fractional sky cover (cloud fraction) and cloud fraction by cloud thickness were downloaded from the ARM Archive for the data analysis (Morris 2015). The TSI was the only other cloud imager that operated at ARM NSA during the deployment of the ICI3, but was limited to periods with sufficient sunlight which prevented winter-time operation.

Multifilter Rotating Shadowband Radiometer

The Multifilter Rotating Shadowband Radiometer (MFRSR) is a passive radiometer that observed the direct normal, diffuse horizontal, and total horizontal solar irradiance at wavelengths of 415, 500, 615, 673, 870, and 940 nm. An image of a MFRSR installed at ARM SGP is shown in Figure 7-18 (b). From its measurements, a value-added product of cloud fraction is derived (Turner & Min 2004). Since these data use measurements over the entire sky dome, this instrument only gives an average sky cloud fraction. The cloud fraction value-added-product was downloaded from the ARM Archive and used in these data comparisons (Shi et al. 2015).

Sky Radiometers for Downwelling Radiation

The SKYRAD is a collection of radiometers that measure continuous broadband shortwave (solar), longwave (infrared), and ultraviolet irradiances. An image of this instrument at ARM SGP is shown in Figure 7-18 (c). The shortwave flux is analyzed using the Long algorithm to produce measurements of cloud fraction (Long & Ackerman 2000; Long et al. 2006; Long 2004; Knuteson et al. 2004). Similar to the MFRSR, this instrument produces a measurement that relates to the average sky cloud fraction. These value-added-product data were downloaded from the ARM Archive and used in these data comparisons [14].

Ceilometer Cloud LIDAR

The ceilometer (CEIL) is a LIDAR sensor that measures cloud-base height, cloud presence, and vertical visibility. As an active instrument the CEIL can operate year round producing both summer and winter-time cloud data. These data were processed to produce a cloud detection parameter that was then averaged in time to provide an estimate of cloud amount. Figure 7-19 (a) shows an image of a CEIL installed at ARM SGP. Clouds were considered present if the CEIL cloud flag was active, or if either of the CEIL obscuration flags were active. The latter of these would be a case of fog where there is a cloud with its base at the ground. To convert a zenith cloud detection to a cloud fraction, the cloud detections were averaged over time to produce a temporal cloud fraction. These data can be compared to a spatial cloud fraction if sufficiently long time periods are used (Kassianov 2005). Cloud detection data were downloaded from the

ARM Archive and processed for temporal cloud fraction and for the data comparison (Morris & Ermold 2015).

Micropulse LIDAR

The Micropulse LIDAR (MPL) is another active cloud measurement instrument that operated at ARM NSA during the deployment of the ICI. Like the CEIL, this system is a LIDAR system that detects clouds at the zenith, an image of the optical components of this instrument is shown in Figure 7-19 (b). The cloud mask images were downloaded from the ARM Archive (Sivaraman & Riihimaki 2015) and processed to produce a cloud detection parameter that was then averaged over time to produce a cloud fraction. The cloud fraction based on the MPL cloud mask did not show good comparison to any of the instruments. This could be due to the prevalence of low clouds at ARM NSA since the lowest cloud-detection bin for the MPL was near 520 meters above ground level (Sivaraman & Riihimaki 2015). This idea is supported by the fact that during periods where the CEIL detected fog and near-ground clouds, the MPL tended to detect clear sky.

Baseline Comparisons

To develop a basis for comparison with the ICI3, baseline comparisons were made between all of the ARM cloud instruments (excluding the MPL). Data have been averaged to provide a daily cloud amount based on times when each both instruments in each instrument pair were operating. These comparisons are presented in Figure 7-20 through Figure 7-26, where scatter plots provide comparisons between the instruments, and the histograms show differences between these instruments. Quantified data for each

of these comparisons are shown in Table 7-9 through Table 7-14. These data include a standard one-sample t-test. For this test, the null-hypothesis was that the difference between the instruments was a zero-mean normal distribution. The alternative hypothesis was rejected based on a 5% significance threshold. To allow for comparison with other cloud imaging studies, the differences in each instrument-pair were cast into terms of okta (Liu et al. 2013; Sun et al. 2011; Wauben et al. 2010).

TSI Versus CEIL The CEIL operates independent of sunlight. The TSI is dependent on scattered sunlight and can only operate during the day. To compare these instruments, the data were limited to periods when the TSI was operating. With this limitation the two instruments compare well, with a correlation above 0.9 and nearly zero mean difference. In a standard t-test the null-hypothesis was rejected. This implies a low probability that the differences between these two instruments are random error. Comparisons are shown in Figure 7-20 and summarized in Table 7-9.

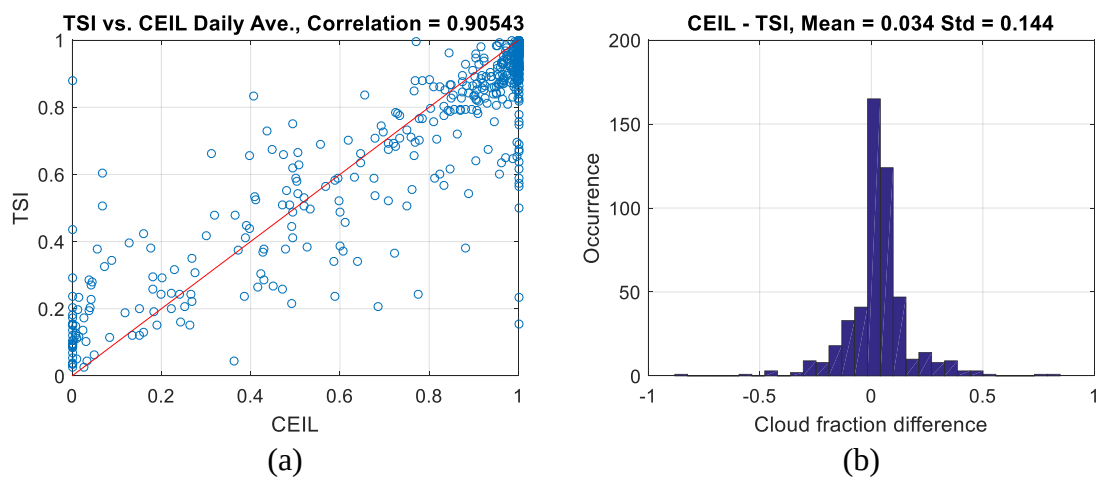


Figure 7-20. Scatter plot of TSI versus CEIL cloud fraction (a) histogram of the cloud difference (b).

Table 7-9. TSI versus CEIL

TSI vs. CEIL	Parameters
Days Compared	502
Correlation	0.905
Mean Difference	0.034
Standard Deviation	0.144
T-Tests Reject, P-value	Yes, 1.4×10^{-7}
Same Okta	46%
± 1 Okta	85%

MFRSR Versus CEIL Similar to the TSI the MFRSR is dependent on scattered sunlight and thus can only operate during the day. To compare this instrument and the CEIL the comparison was limited to only time periods when the MFRSR was operating. The two instruments compared well demonstrating a high correlation of 0.97 and a zero mean difference. For these instruments the t-test failed to reject the null-hypothesis. This implies that there is a high probability the difference between these two instruments are a zero mean random error. The MFRSR versus CEIL comparisons are shown in Figure 7-21 and summarized in Table 7-10.

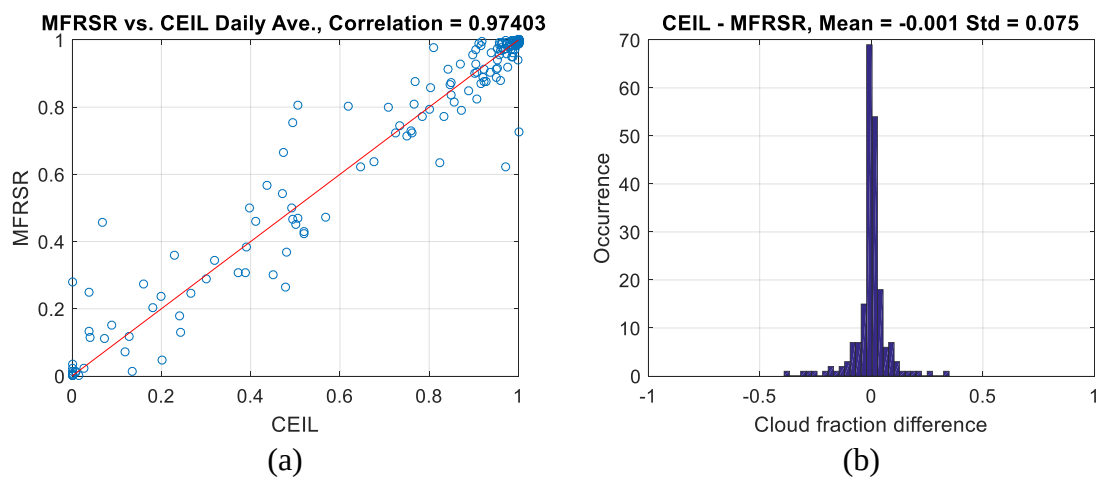


Figure 7-21. Scatter plot of MFRSR versus CEIL cloud fraction (a) histogram of the cloud difference (b).

Table 7-10. MFRSR versus CEIL

MFRSR vs. CEIL	Parameters
Days Compared	205
Correlation	0.974
Mean Difference	-0.001
Standard Deviation	0.075
T-Tests Reject, P-value	No, 0.79
Same Okta	72%
± 1 Okta	93%

SkyRad Versus CEIL The SkyRad cloud fraction is limited to daytime operation.

To compare with the CEIL the data were limited to time periods when the SkyRad produced a cloud fraction. The two instruments compared well with a correlation of 0.91 and a zero mean difference. Relative to the MFRSR there is much more scatter between the SkyRad and the CEIL measurements, in particular during periods of partly cloudy skies. For these instruments the t-test rejected the null-hypothesis. This implies that there is a low probability the difference between these two instruments are a zero mean random error. These comparisons are shown in Figure 7-22 and summarized in Table 7-11.

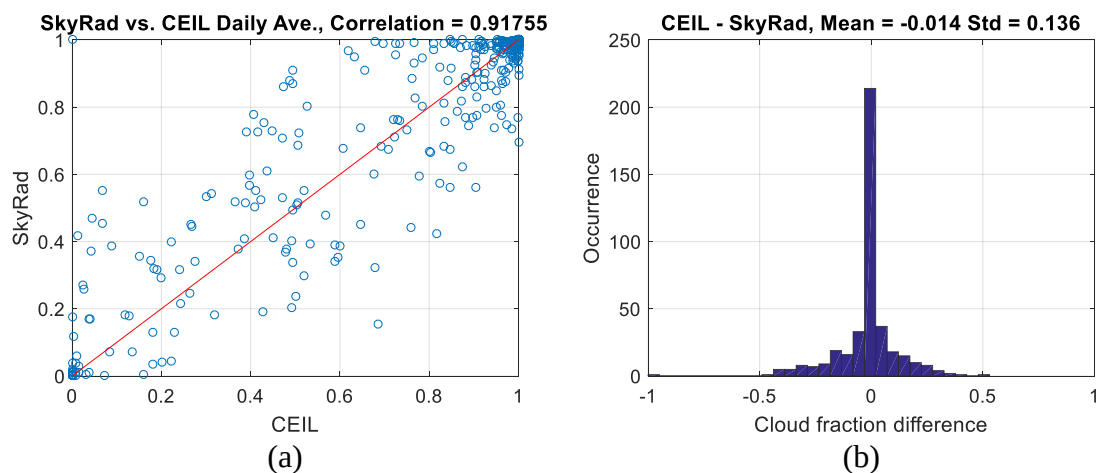


Figure 7-22. Scatter plot of SkyRad versus CEIL cloud fraction (a) histogram of the cloud difference (b).

Table 7-11. SkyRad versus CEIL

SkyRad vs. CEIL	Parameters
Days Compared	414
Correlation	0.919
Mean Difference	-0.014
Standard Deviation	0.136
T-Tests Reject, P-value	Yes, 0.035
Same Okta	61%
± 1 Okta	82%

MPL Versus CEIL To allow comparison between the MPL and the CEIL, only the regions where these two instruments have overlapping sensitivity was used. This comparison was therefore limited to data with cloud-base height above 520 m, as limited by the MPL (Sivaraman & Riihimaki 2015) and data with a cloud-base height below 7.6 km, as limited by the maximum operating height of the CEIL at ARM NSA (Morris & Ermold 2015). Even when limited to this region, the MPL significantly underreported cloud presence, as can be seen in Figure 7-23, where the CEIL frequently reported clouds when the MPL did not.

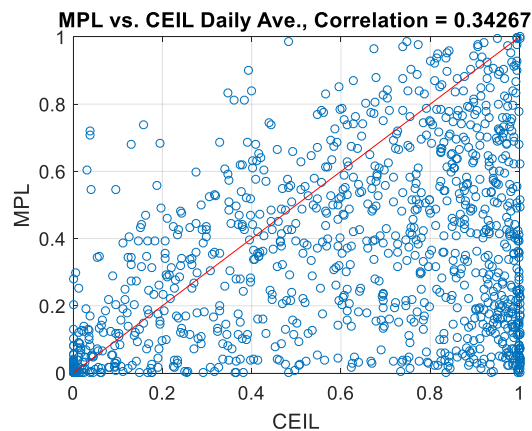


Figure 7-23. Scatter plot of MPL versus CEIL cloud fraction in the 500m AGL to 7.6 km AGL region of cloud-detection overlap.

MFRSR Versus TSI Both the TSI and the MFRSR are limited to daytime only operation. These two instruments show the highest correction of any of the instrument comparisons at 0.98. The t-test failed to reject the null hypothesis, however when observing the scatter data in Figure 7-24 a clear bias can be observed where the TSI never reports fully clear skies. This may be in part due to the whole sky observation of the TSI where there is an increased probability over observing clouds near the horizon in whole sky images. It may also result from a non-linearity in one of the two observation techniques. These comparisons are shown in Figure 7-24 and Table 7-12.

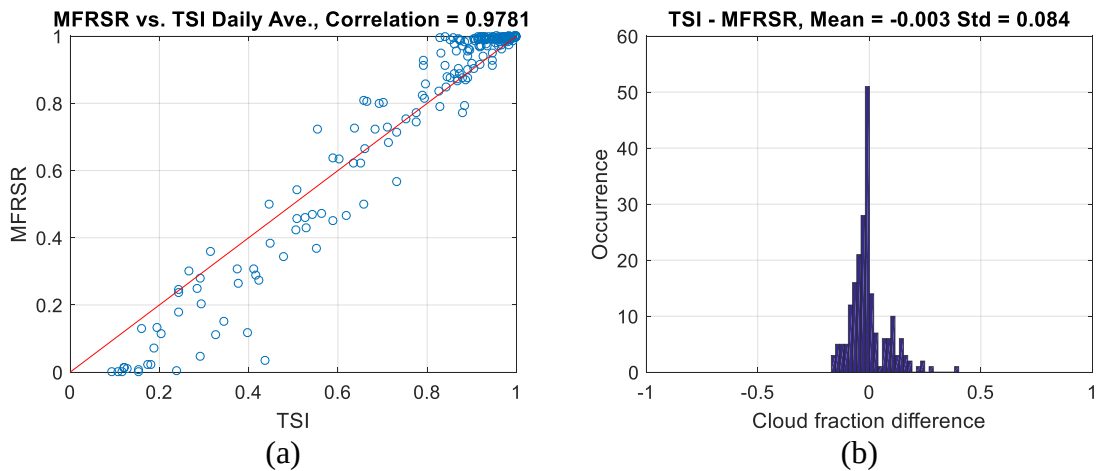


Figure 7-24. Scatter plot of MFRSR versus TSI cloud fraction (a) histogram of the cloud difference (b).

Table 7-12. MFRSR versus TSI

MFRSR vs. TSI	Parameters
Days Compared	209
Correlation	0.978
Mean Difference	-0.003
Standard Deviation	0.084
T-Tests Reject, P-value	No, 0.65
Same Okta	52%
± 1 Okta	96%

SkyRad Versus TSI Both the TSI and the SkyRad cloud data project have the same limitation to daytime only operation and therefore comparison on these two instruments are straightforward. These two instruments show high correlation at 0.91. The t-test rejected the null hypothesis. Similar to the comparison of the TSI and MFRSR, there is a clear bias where the TSI never reports fully clear skies, this leads to a curve in the comparison for skies with low cloud fraction. These comparisons are shown in Figure 7-25 and Table 7-13.

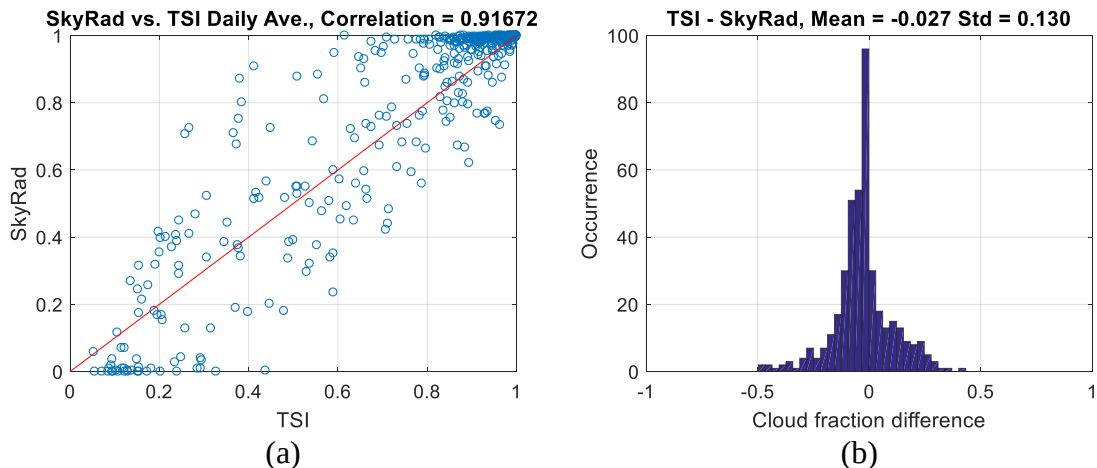


Figure 7-25. Scatter plot of SkyRad versus TSI cloud fraction (a) histogram of the cloud difference (b).

Table 7-13. SkyRad versus TSI

SkyRad vs. TSI	Parameters
Days Compared	418
Correlation	0.917
Mean Difference	-0.027
Standard Deviation	0.130
T-Tests Reject, P-value	Yes, 2.5×10^{-5}
Same Okta	40%
± 1 Okta	84%

SkyRad Versus MFRSR The SkyRad and the MFRSR are both passive radiometers that use similar indirect measurements to measure cloud fraction. The comparison between these two instruments show one is very close to the 1:1 and have a correlation of 0.95, and failure to reject the null hypothesis in the t-test. There is a large amount of residual scatter in particular during periods of partly cloudy skies. This scatter is likely present in the SkyRad data, since all comparisons with this instrument tend to show a similar large scatter.

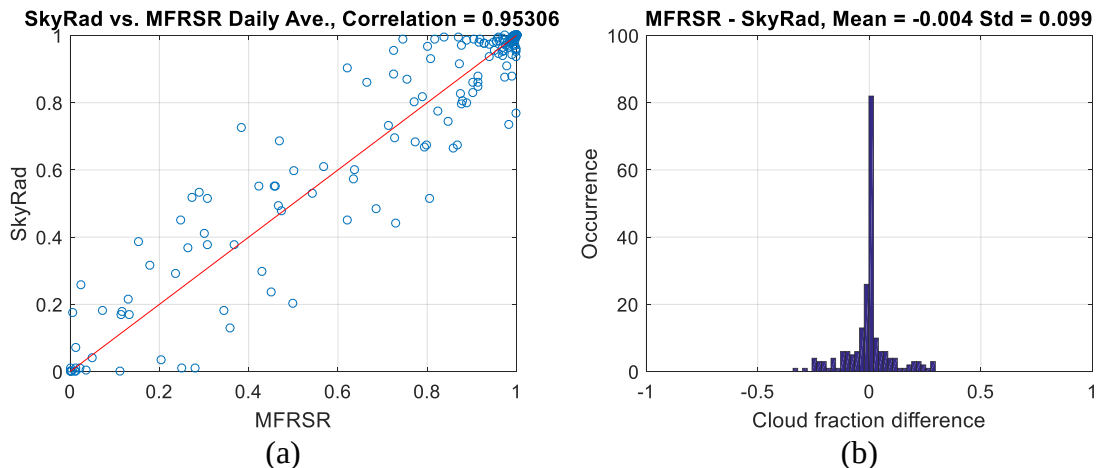


Figure 7-26. Scatter plot of MFRSR versus SkyRad cloud fraction (a) histogram of the cloud difference (b).

Table 7-14. MFRSR versus SkyRad

MFRSR vs. SkyRad	Parameters
Days Compared	208
Correlation	0.953
Mean Difference	-0.004
Standard Deviation	0.099
T-Tests Reject, P-value	No, 0.59
Same Okta	63%
± 1 Okta	85%

Summary of ARM Instrument Comparisons Overall, these instruments show very good comparisons with correlations of 0.90 or greater, and low mean difference. The SkyRad and MFRSR compare well, and t-tests failed to reject the null-hypothesis, suggesting any differences are zero-mean Gaussian. The null-hypothesis was not rejected in comparisons of the SkyRad with the TSI and the SkyRad with the CEIL, suggesting there is a bias between the SkyRad and these two instruments. Table 7-15 provides a summary of the correlation coefficient and p-value for the ARM instrument comparisons, the data in bold are cases where the t-test failed to reject the null-hypothesis.

Table 7-15. Inter-comparisons of the co-located ARM cloud instruments

Instrument	CEIL		MFRSR		SkyRad	
	Corr	P-value	Corr	P-value	Corr	P-value
MFRSR	0.97	0.79				
SkyRad	0.92	0.03	0.93	0.59		
TSI	0.91	1.4E ⁻⁷	0.98	0.65	0.92	2.5E ⁻⁵

From this summary it can be seen that the MFRSR compares well with all other instrument, high correlation and p-value. The other instruments are biased when compared with each other, but not with the MFRSR. This suggests there are real differences between these instruments with the MFRSR providing a data product that lies between the data produced from all other instruments. The TSI and the CEIL produced a data product that was the least similar, based on the lowest correlation and lowest p-value.

Overall okta differences showed 80% of the data reported ± 1 okta or less, and were typically within the same okta more than 50% of the time. It is important to note that these comparisons were limited to time periods when both instruments were

operating. Often this significantly limited the numbers of days in the comparisons or limited the time periods to particular times such as only when the sun was above the horizon for visible instruments.

Comparisons of ICI and the ARM Instruments

These comparisons were taken between the existing ARM instruments and the ICI during the summer 2012 to summer 2014 experiment. To keep with consistency with the previous inter-instrument comparisons, data have been limited to only times when both instruments were operating. The ICI3 also closed its hatch when rain was detected. In previous data analysis it had been assumed that there was a cloud fraction of 1 during these times. However, when this assumption was made it decreased the correlation between the ICI3 and co-located instruments. Therefore, rather than making this assumption, those data were simply removed from this comparison.

Comparisons of All ICI Processing Routines The ICI operated with a variety of cloud detection sensitivities that correspond to bins of maximum cloud optical depth. From the negative residual radiance analysis, it was shown that the cloud detection threshold could be set as low as level 3 for the adaptive algorithm, and as low as level 4 for the directly processed data. Initial analyses were conducted observing the p-value of a t-test and instrument correlation. These data showed that the best comparison with other instruments was observed for an ICI3 cloud detection threshold of level 5 (cloud OD>1) when using the direct cloud detection algorithm and a threshold 4 (cloud OD>0.5) when using the adaptive cloud processing algorithms. The results of these comparisons are

shown in Table 7-16. In this table the correlation and p-value for comparisons between each co-located instrument and each ICI3 calibration / processing pair are shown. Data that are listed in bold font are sets where the t-test failed to reject the null-hypothesis that the differences were zero-mean Gaussian. Data rows highlighted with a gray background are calibration/processing method sets where at least three of the four instrument comparisons failed to reject the null-hypothesis, and high correlations were observed between the reported cloud data.

Table 7-16. Comparisons of the ICI with co-located ARM cloud instruments

Instrument	CEIL		MFRSR		SkyRad		TSI	
	Corr	P-value	Corr	P-value	Corr	P-value	Corr	P-value
2016S v1	0.85	1.2E ⁻⁶	0.77	0.002	0.85	0.003	0.89	1.5E ⁻¹⁸
2016S v4	0.95	0.67	0.92	0.52	0.90	0.11	0.92	0.27
2016S v4m	0.94	0.03	0.93	0.18	0.93	0.76	0.93	0.11
2016BB v1	0.91	0.10	0.92	0.40	0.91	0.86	0.93	3.3E ⁻⁸
2016BB v4	0.94	0.79	0.92	0.70	0.91	0.06	0.91	0.87
2016BB v4m	0.92	0.71	0.90	0.03	0.89	0.9	0.91	7.3 E ⁻⁵
2012S v1	0.92	2.0E ⁻⁵	0.91	0.05	0.89	4.6E ⁻⁷	0.93	0.47
2012S v4	0.93	0.11	0.92	0.54	0.91	0.41	0.91	0.08
2012BB v1	0.92	0.24	0.91	0.14	0.89	0.007	0.92	0.03
2012BB v4	0.93	0.28	0.91	0.81	0.91	0.25	0.92	0.15
2016Best v1	0.91	0.02	0.92	0.35	0.91	0.60	0.93	3.6E ⁻¹⁰
2016Best v4	0.95	0.42	0.92	0.68	0.91	0.11	0.92	0.46
2016Best v4m	0.93	0.07	0.91	0.03	0.90	4.2E ⁻⁷	0.92	0.05
Band51 v1	0.85	1.8E ⁻⁶	0.78	0.003	0.85	7.1E ⁻⁴	0.89	4.9E ⁻¹⁹
Band51 v4	0.94	5.9E ⁻⁹	0.92	0.07	0.89	1.4E ⁻⁶	0.93	0.82
Band51 v4m	0.94	0.003	0.93	0.02	0.91	2.2E ⁻⁵	0.93	0.30
SVM v1	0.90	4.3E ⁻²³	0.85	0.98	0.86	3.5E ⁻⁵	0.92	0.51
SVM v2	0.92	8.8E ⁻¹⁰	0.86	1.3E ⁻⁵	0.78	1.4E ⁻⁴	0.83	3.3E ⁻⁵

From these data it can be seen that the 2016S calibration had the best performance of the data sets. It can also be seen that the v4 algorithm improved data accuracy. This is especially noticeable in some of the data sets that are known to be biased (in comparison

to the AERI). For example, Band51 had very low performance using the v1 (direct data processing) method, but compared well with the v4 algorithm. There are still biases present in these data sets, as shown by the rejection of the null-hypothesis in all but a few cases. The non-radiometric SVM-based algorithm performed quite well.

The following sections present the results of the ICI3 calibration / processing method sets that had the highest performance. For all but the CEIL, this was the 2016S v4m, the 2016 laboratory calibration with the adaptive gradient and time data processing method using a 60-minute history of clear-sky data. The 2016S v4 data compared best to the CEIL. These data used the v4 algorithm with only a 3-minute history of clear-sky data. Each comparison presents the ICI3 data with the best comparison.

ICI3 Versus TSI To compare the ICI3 and the TSI only periods when the TSI was operating were selected. This removed ICI3 data collected during the winter and nighttime when no sunlight was present. The ICI and the TSI show good agreement with a correlation of 0.93, and a p-value of 0.11 leading to a failure to reject the null-hypothesis. This suggests that these data are largely unbiased. The non-linearity that was observed between the TSI and other ARM instruments is present with the ICI3 data.

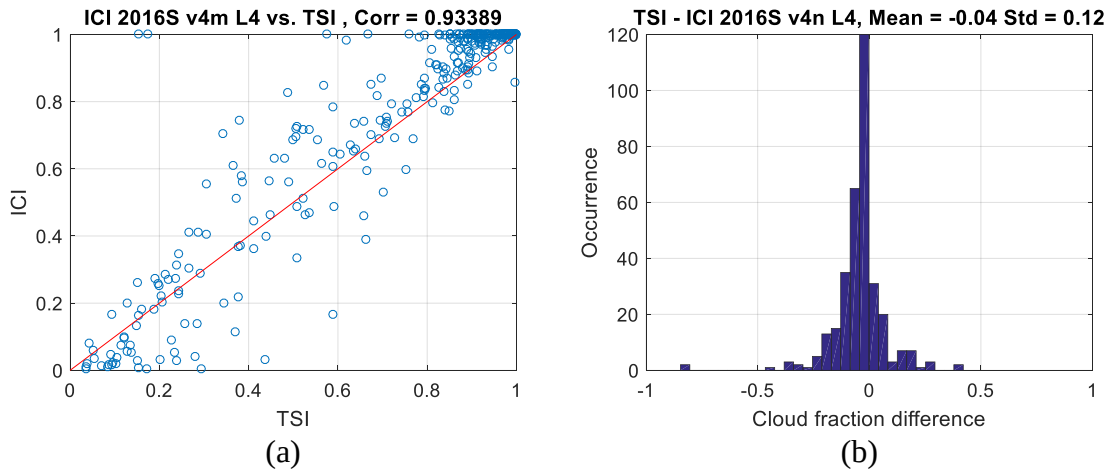


Figure 7-27. Scatter plot of ICI3 versus TSI cloud fraction (a) histogram of the cloud difference (b).

Table 7-17. ICI versus TSI

ICI 2016S v4 vs. TSI	Parameters
Days Compared	344
Correlation	0.93
Mean Difference	-0.04
Standard Deviation	0.12
T-Tests Reject, P-value	No, 0.11
Same Okta	52%
± 1 Okta	91%

SkyRad Versus ICI To compare the ICI3 and the SkyRad data were limited to periods when the SkyRad reported a cloud fraction data product. This removed winter and nighttime data. The ICI and the SkyRad show good agreement with a correlation of 0.93, and a p-value of 0.13 leading to a failure to reject the null-hypothesis. Similar to comparisons of the SkyRad and the other ARM instruments there is a large spread in the data in particular during partly cloudy skies. This scatter is likely in the SkyRad data.

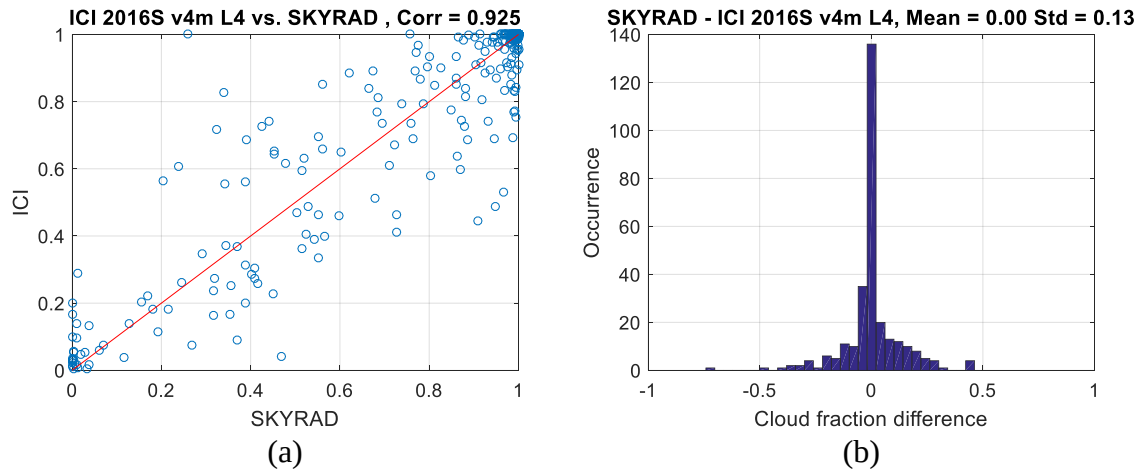


Figure 7-28. Scatter plot of SkyRad versus ICI cloud fraction (a) histogram of the cloud difference (b).

Table 7-18. SkyRad versus ICI

SkyRad vs. ICI 2016S v4	Parameters
Days Compared	298
Correlation	0.925
Mean Difference	0.00
Standard Deviation	0.13
T-Tests Reject, P-value	No, 0.76
Same Okta	63%
± 1 Okta	87%

MFRSR Versus ICI To compare the ICI3 and the MFRSR data were limited to periods when the sun was above the horizon. The ICI and the MFRSR showed good agreement with a correlation of 0.94, and a p-value of 0.18 leading to a failure to reject the null-hypothesis. The MFRSR and the ICI produced very similar cloud products during the limited times when they both operated (the MFRSR requires sunlight).

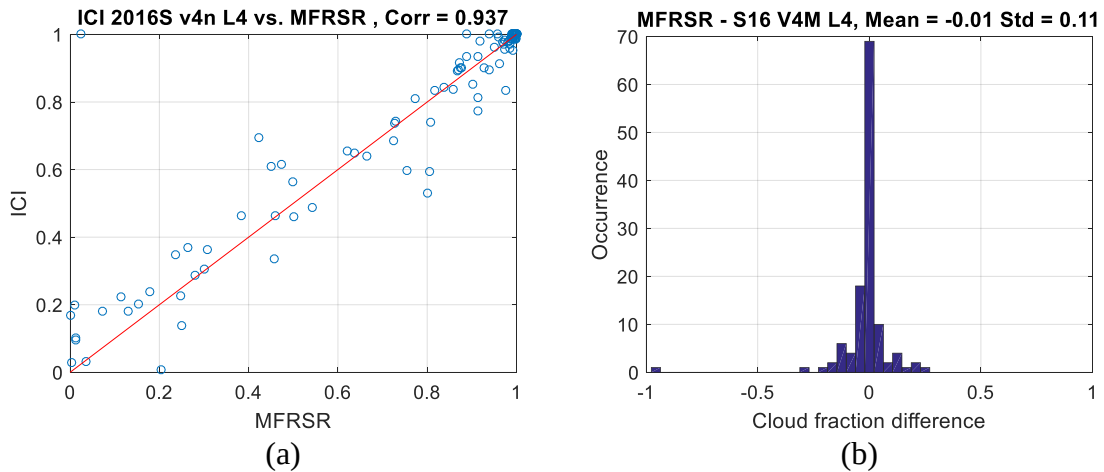


Figure 7-29. Scatter plot of MFRSR versus ICI cloud fraction (a) histogram of the cloud difference (b).

Table 7-19. MFRSR versus ICI

MFRSR vs. ICI 2016S v4	Parameters
Days Compared	128
Correlation	0.937
Mean Difference	-0.01
Standard Deviation	0.11
T-Tests Reject, P-value	No, 0.18
Same Okta	76%
± 1 Okta	96%

CEIL Versus ICI Both the CEIL and the ICI3 operate throughout the entire year and therefore the comparison of these data did not remove winter and nighttime data. The CEIL data were considered cloudy during periods of obscuration (likely fog). The ICI and the CEIL showed the highest correlation observed with ICI3 data at 0.95. The p-value is also high and 0.67 leading to a failure to reject the null-hypothesis. For most operating periods the ICI3 and the CIEL showed very little scatter; however, there were significant outliers where the instruments produced very different data products.

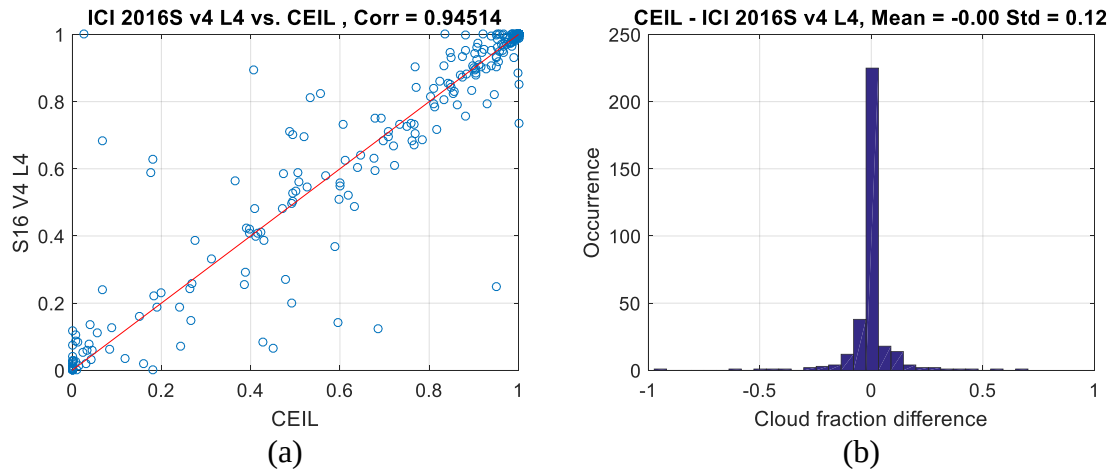


Figure 7-30. Scatter plot of ICI versus CEIL cloud fraction (a) histogram of the cloud fraction difference (b).

Table 7-20. ICI versus CEIL

ICI 2016S v4 vs. CEIL	Parameters
Days Compared	536
Correlation	0.945
Mean Difference	-0.00
Standard Deviation	0.12
ICI Threshold Level	4
T-Tests Reject, P-value	No, 0.67
Same Okta	72%
± 1 Okta	92%

Analysis of the ICI SVM Processor

The implementation of a SVM in the ICI data processing started as an effort to develop a method to find clouds and clear sky based on a radiometric differences along with other parameters to improve cloud identification. As the SVM was developed, sensitivity analyses on the input parameters showed including the radiometric parameters only resulted in small improvements (2 to 3%) in accuracy. Therefore, two SVM cloud detection systems were developed that allowed the ICI to operate independently of external instruments and without an absolute radiometric calibration. Figure 7-31 shows

the results of the SVM1 output, which tends to underreport clouds compared to the CEIL.

Figure 7-32 shows the result of SVM2 when compared to the CEIL, showing improved correlation. The positive bias suggests this SVM may have increased sensitivity.

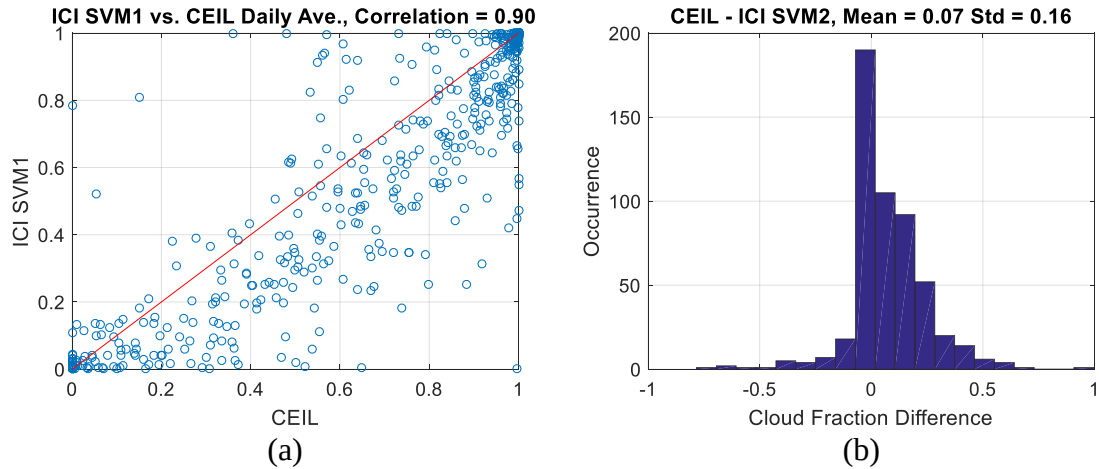


Figure 7-31. The non-radiometric ICI3 SVM1 versus the CEIL showing good comparison as seen the scatter plot (a) and difference histogram (b).

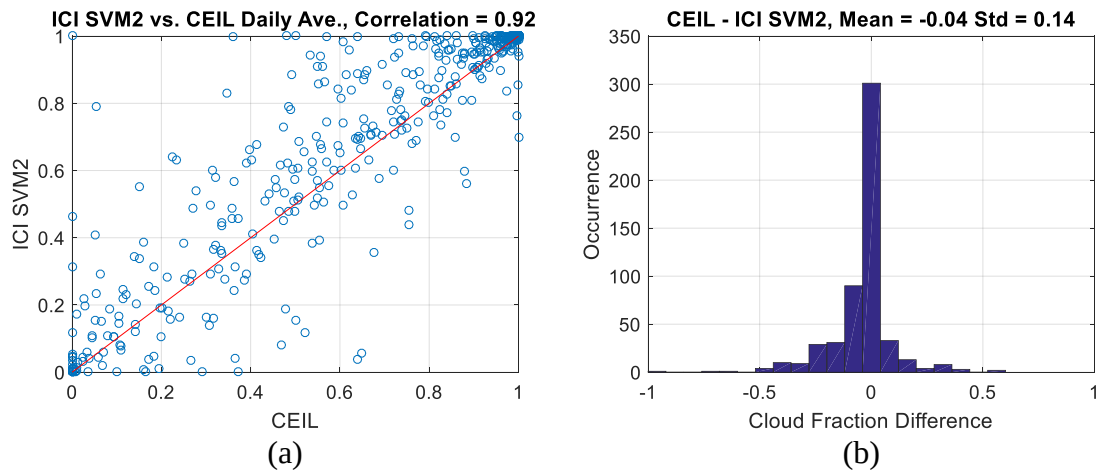


Figure 7-32. The non-radiometric ICI3 SVM2 versus the CEIL showing good comparison as seen in the scatter plot (a) and difference histogram (b).

Cloud Occurrence Diagrams (Smile Diagrams)

Cloud occurrence diagrams for the Arctic tend to show a trend where the most probable events are clear sky or fully cloudy sky which decreasing probability in between. This has led to these diagrams being referred to as smile diagrams in the Arctic, where most of the time the sky tends to be very clear or very cloudy, since they can resemble a cartoonish smile. In the following section cloud occurrence has been calculated for the ARM cloud instruments and the ICI using daily cloud fraction data.

Figure 7-33 shows a histogram of cloud occurrence as detected by each of the ARM instruments during the full ICI3 deployment. It is interesting to note that the TSI very seldom reported clear skies, where all other instruments often reported clear skies. In fact, all instruments but the TSI tended to have very similar diagrams, showing largely clear skies and fully overcast skies. The TSI rather tended to report a continuum of cloud fraction, with clear skies the least likely result. This difference could be due to the whole sky nature of the TSI where the probability of having a completely clear sky is low due to the large region of the sky that is observed by the TSI. These near horizon clouds may go un-noticed by the other cloud sensing instruments.

Figure 7-34 shows a series of cloud occurrence histograms detected by different ICI3 data processing methods during the ICI3 deployment. In Figure 7-34 the top row contains smile diagrams of cloud fraction occurrence using the radiometric data processing (2016S v4) for both TSI-matched time periods (a) and all time periods (b). The middle row shows the non-radiometric SVM version 1 data processing for both TSI matched time periods (c) and all time periods (d). The bottom row shows the non-

radiometric SVM version 2 with higher sensitivity to thin clouds for both TSI matched time periods (e) and all time periods (f). These ICI3 data processing methods tended to report very similar occurrences of cloud fraction as the other (non-TSI) instruments for all data processing methods. However, the SVM2 method tends to report more clouds.

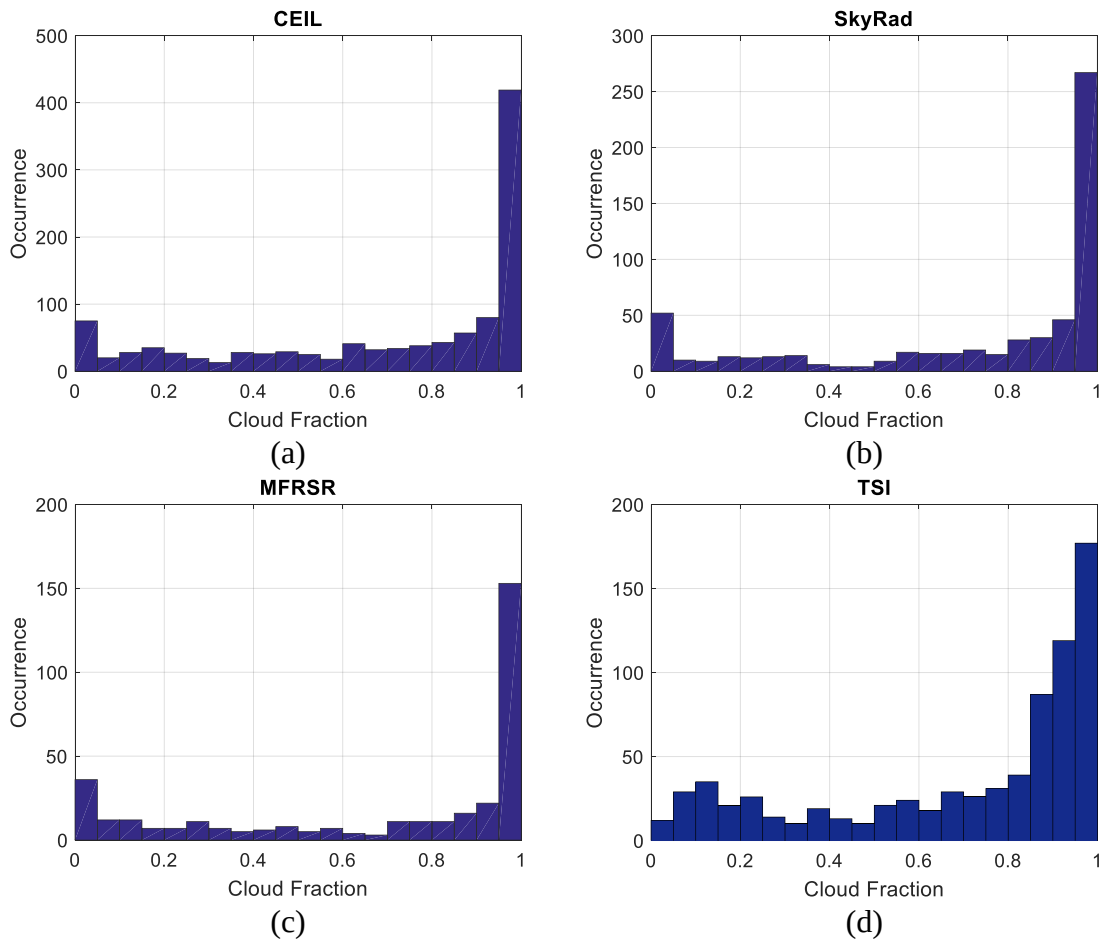


Figure 7-33. Cloud Fraction at ARM NSA as measured by the ARM cloud instruments in terms of sky coverage.

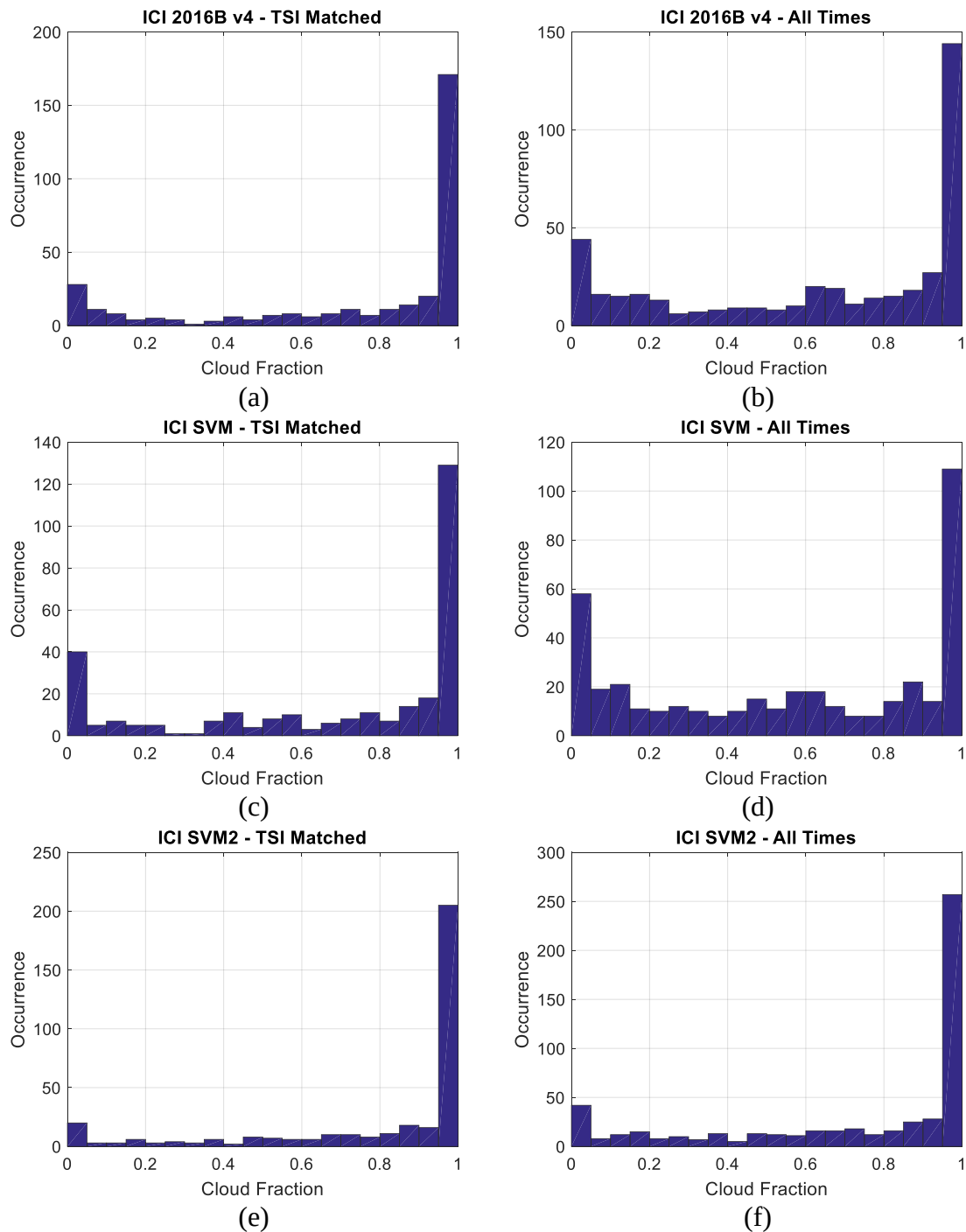


Figure 7-34. Smile diagrams showing cloud fraction occurrence at ARM NSA measured by the ICI3. The top row shown the radiometric data processing for both TSI match time periods (a) and all time periods (b). The middle row shows the non-radiometric SVM version 1 data processing for both TSI matched time periods (c) and all time periods (d). The bottom row shows the non-radiometric SVM version 2 with higher sensitivity to thin clouds for both TSI matched time periods (e) and all time periods (f).

Extended Sensitivity of the ICI3

To achieve the best correlations with the ARM instruments, the ICI3 used the adaptive processing techniques with thresholds set to level 4 ($OD > 0.5$). However, based on the uncertainty analysis conducted in Chapter 6 and the negative residual radiance analysis conducted earlier in this chapter, there is a gap between the uncertainty in the ICI3 and threshold 4. This suggests that the ICI3 was able to detect clouds that went undetected with the co-located ARM instruments. This is consistent with findings from other LWIR cloud imagers, where the sensitivity to thin clouds has to be decreased to improve correlation with co-located instruments (Morris et al. 2011; Smith & Toumi 2008). Owing to the careful sensitivity and performance analysis of the ICI3, we have confidence that these signals were not noise and therefore can be considered valid cloud detections. In the following section, these thin clouds detected by the ICI3 are presented.

Comparison with ARM Instruments

In these figures the ICI3 tended to report consistently more clouds during periods of mixed clouds and periods that were previously considered clear skies. It seems that these are high thin clouds that are missed by other ARM instruments. Because the MPL saw high thin clouds that were missed by the CEIL, a metric of the Max Active Cloud based on the maximum of the CEIL or MPL cloud detection was calculated. When comparing this value to the higher-sensitivity ICI3 data, the correlation improved, but the difference distribution was still biased toward the ICI3, as shown in the scatter plot and

difference histogram in Figure 7-37. This adds support to the claim that the ICI3 detected thin arctic clouds that were not observed by other ARM instruments.

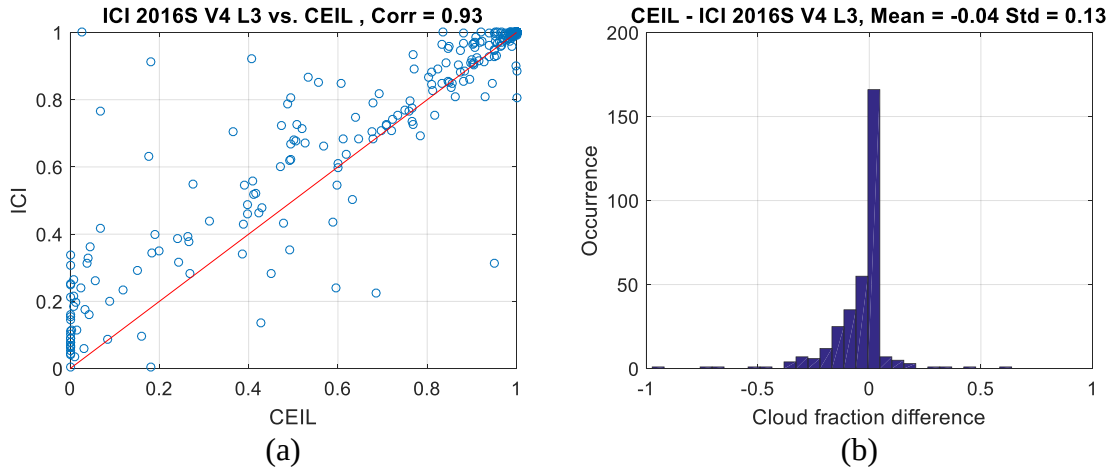


Figure 7-35. The ICI3 higher cloud detection versus the CEIL. The ICI v4 L3 (decreased cloud radiance threshold) is more sensitive to thin clouds.

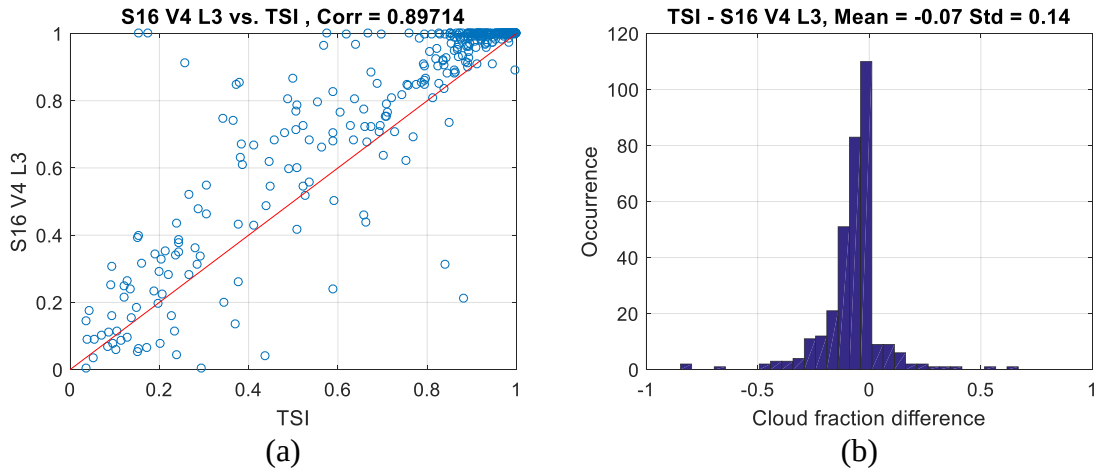


Figure 7-36. The ICI3 higher cloud detection versus the TSI. The ICI v4 L3 (decreased cloud radiance threshold) is more sensitive to thin clouds.

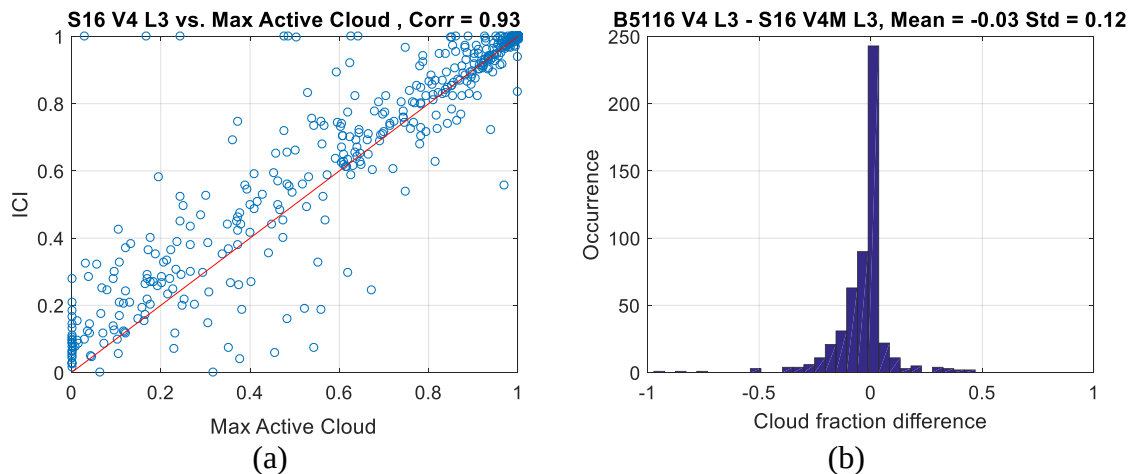


Figure 7-37. The ICI3 higher cloud detection versus the Max Active Cloud. The ICI v4 L3 (decreased cloud radiance threshold) is more sensitive to thin clouds.

Smile diagram differences for these data sets show a consistent increase in cloud cover at the lower cloud fraction levels. This suggests that these were thin clouds in scenes that would otherwise have been classified as cloud free, and not an increase in sensitivity to cloud edges or other scattered cloud effects.

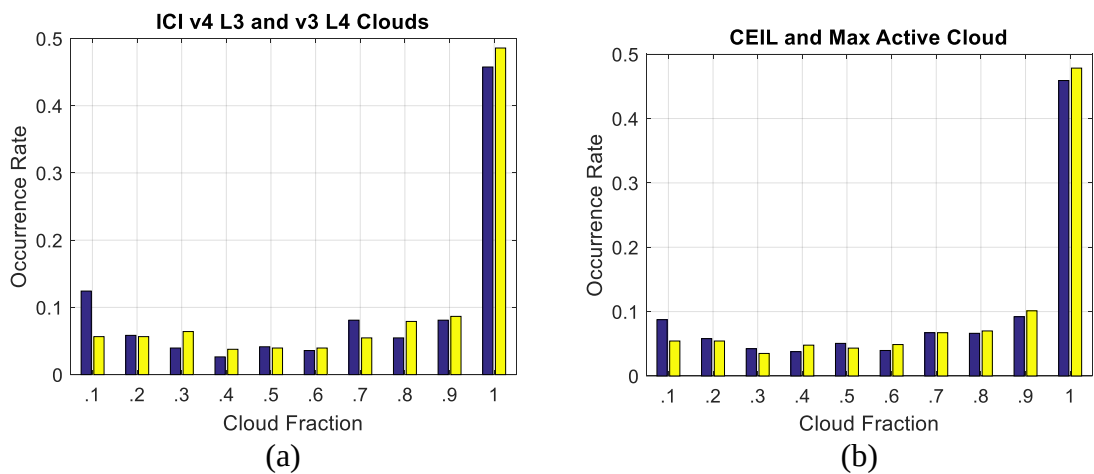


Figure 7-38. The ICI3 higher cloud detection versus the Max Active Cloud. The ICI v4 L3 (decreased cloud radiance threshold) is more sensitive to thin clouds.

To further address the question of thin clouds, the annual change in cloudiness was observed. The monthly average cloud fraction for the increased-cloud-sensitivity ICI3 data are shown in Figure 7-39 with level 4 (standard sensitivity) in blue and level 3 (higher sensitivity) in yellow. Similar data for the CEIL and the Max Active Cloud are shown in Figure 7-40. Both of these data plots show similar trends in annual cloudiness.

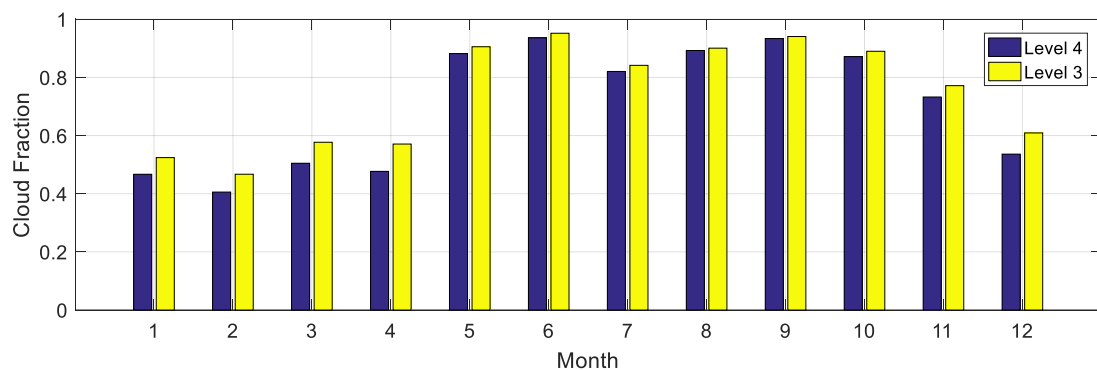


Figure 7-39. The monthly average cloud fraction for the increased-cloud-sensitivity ICI3 data with level 4 standard sensitivity in blue, and level 3 high sensitivity in yellow.

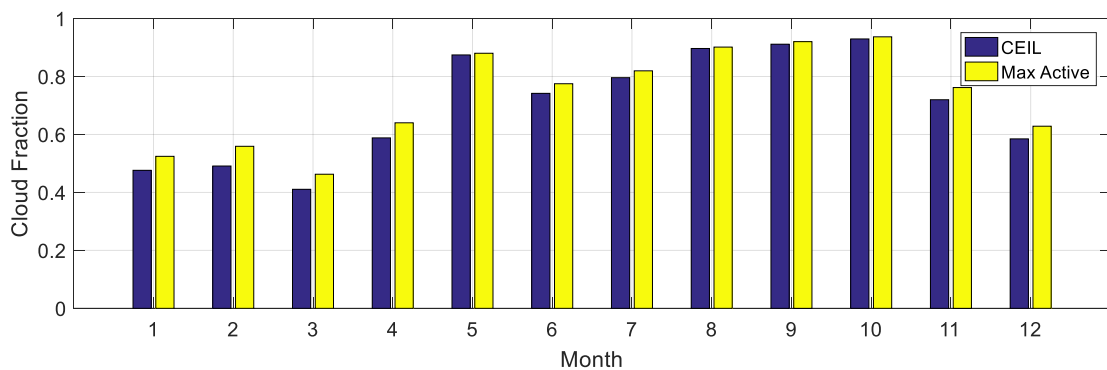


Figure 7-40. The monthly average cloud fraction for the increased-cloud sensitivity-LIDAR data and standard CEIL data in blue, and Max Active Cloud in yellow.

To determine if these two high-sensitivity data sets show increases in cloud cover at the same times throughout the year, the difference was calculated between the standard sensitivity and high sensitivity for each of these data sets. Both these data sets show

similar trends, with the greatest increases occurring during the cold winter months. These periods are the least cloudy of the ARM NSA measurements. This adds further support that the ICI3 detected thin winter clouds.

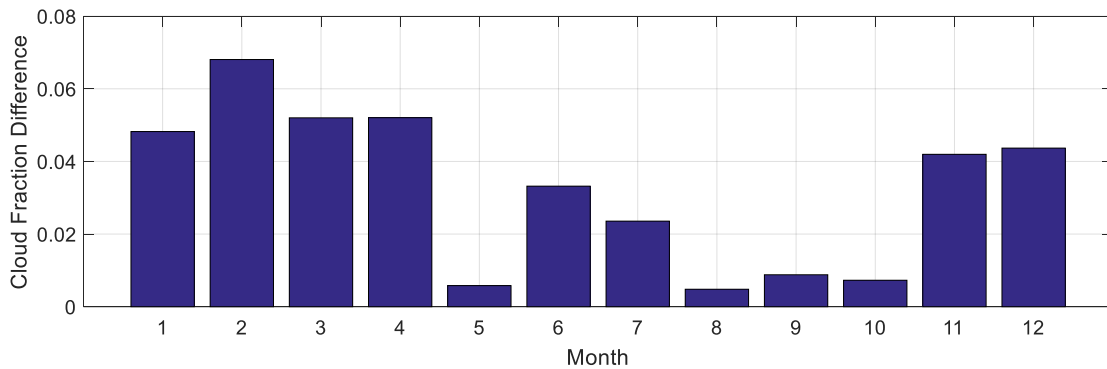


Figure 7-41. The monthly cloud fraction difference between ICI3 level 3 high sensitivity data and the level 4 standard sensitivity data.

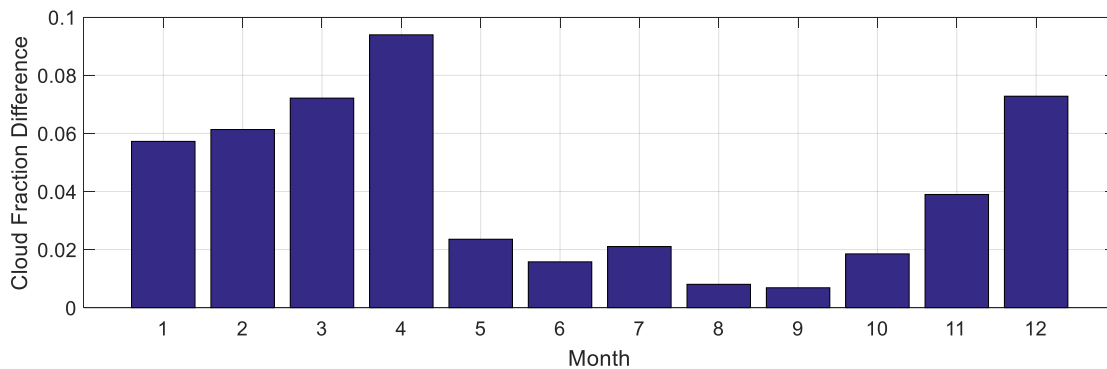


Figure 7-42. The monthly cloud fraction difference between Max Active Cloud high sensitivity data and the CEIL standard sensitivity data.

Both the increased-sensitivity ICI3 data and the Max Active Cloud data show similar changes with increased cloud sensitivity: high clouds in the Max Active Clouds, and thin clouds in the ICI3. The decreases in similar parts of the smile diagram and the similarity in the annual trends both suggest that the ICI3 demonstrated the capability of sensing thin, clouds that were not measured by other cloud sensing instruments.

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CONCLUSIONS

Goal of this Project

The primary objective of this project was to develop an understanding of the performance, sensitivity, and scientific results of the Third-Generation Infrared Cloud Imager (ICI3) during its deployment at the Atmospheric Radiation Measurement (ARM) program site at the North Slope of Alaska (NSA) near Barrow, AK in 2012-2014. The ICI3 was developed to measure cloud cover through both the Arctic winter and summer using the same measurement technique based on long-wave infrared (LWIR) imaging. Cloud cover in the Arctic is an important, but poorly understood and often unavailable, component of climate models. Ground-based LWIR cloud imaging has the ability to help fill these gaps.

Building and operating an LWIR imager in the Arctic required us to overcome the challenges of this environment. Of particular interest to accurate LWIR imaging was understanding the long-term reliability of the system calibration and data processing routines. This was of particular difficulty because of the severe temperature changes experienced in the Arctic. Another challenge was that weak emission from the cold, dry Arctic atmosphere pushed the LWIR camera used in the ICI3 to its operational limits (in fact well beyond the limits conceived by the camera manufacturer).

Contributions of this Project

The two-year record of arctic clouds from the ICI3 is a significant contribution to the arctic cloud science community. Summaries of preliminary versions of these data have been made publicly available as part of the ARM database. ARM program representatives have expressed interest in a complete data set that includes multiple data processing methods. This is a significantly large set of data and conversations are ongoing on how to make these data publicly available. This larger data set could be used by other researchers in Arctic climate studies. It could be used to further validate the ICI3 data processing routines against experimental routines in other instruments. These data could also be used to aid the development of future data processing routines for the co-located ARM instruments or LWIR cloud imagers.

Understanding of Instrument Operation

The deployment at ARM NSA from July 2012 through July 2014 has led to a greatly improved understanding of how to operate the ICI systems in the Arctic. Through a careful data processing sensitivity analysis, including both the camera and the atmosphere, an understanding of the uncertainty in the ICI3 data products has been developed. This sensitivity analysis has been supported by studying the various data outputs of the ICI3 in comparison to co-located radiometric and cloud sensors.

Instrument Accuracy Analysis The careful analysis of sources of uncertainty in the ICI3, including a radiometric model of the bolometer-based camera, is a significant contribution of this project. To develop this understanding, the operation of the ICI3

camera was carefully characterized along with the full optical system, including the lens, filter, and detector. The sources of uncertainty external to the ICI3 were also investigated. This study has shown that the uncertainty in these cloud imaging systems leads to difficulty consistently detecting the thinnest of cirrus clouds when using the standard radiometric techniques.

The minimum-detectable cloud based only on instrument noise (NER and FFC) was 0.14 OD, close to the human visual limit for sun-illuminated cirrus clouds. For the standard technique, the theoretical limit for consistent cloud detection based on a 99% detection probability (SNR of 5) was an optical depth of 0.56 at the zenith. In operation, this limit was estimated to be between 0.49 and 0.88. This minimum-detectable cloud was worse than the intended design goals of this instrument. This demonstrated the need for adaptive algorithms and led to the implementation of a gradient-and-time (v4) algorithm and the support vector machine cloud classifier.

Based on these results, the uncertainty analysis technique should be implemented for other ICI instruments, such as those currently deployed by the NASA JPL. These sites use different methods of estimating precipitable water vapor and surface temperature, along with different implementations of the LWIR cameras. It is expected that this will lead to unique sets of uncertainties for these sites and the values determined at ARM NSA should not be applied to these other instruments.

Radiometric Comparisons with the AERI The comparison to the AERI showed that throughout a two-year period, the ICI3 instrument was able to remain within $\pm 1.2 \text{ W}/(\text{m}^2 \text{ sr})$ of the AERI integrated radiance. Much of this uncertainty can be

accounted for in the $\pm 1.01 \text{ W}/(\text{m}^2 \text{ sr})$ expected uncertainty due to the uncertainty in the ICI3 spectral response function. This uncertainty could be reduced through measurement of the ICI3 camera's spectral response function, which is being pursued at present. This process also showed that the spectral radiometric data from the AERI could be used to derive the spectral response function of a LWIR camera via a genetic algorithm. Future measurements of the ICI3 camera's spectral responsivity will determine the accuracy of the spectral response derived in this way for the ICI3.

Comparisons with Co-Located Cloud Instruments Through comparison with co-located cloud sensors, the consistency of the ICI3 cloud fraction in relation to cloud fraction produced by the co-located sensors has been developed. Comparisons were conducted between the ICI3 and the Total Sky Imager (TSI), the Multifilter Rotating Shadowband Radiometer (MFRSR), the Sky Radiometer (SKYRAD), and the ceilometer (CEIL). It was shown that the ICI3 had a correlation coefficient better than 0.925 with all co-located cloud instruments, and better than 0.935 with the MFRSR and the CEIL. However, achieving these high correlations required the ICI3 cloud detection threshold to be increased, reducing the ICI3 sensitivity to thin clouds. This is consistent with other comparisons made between similar instruments and other LWIR cloud sensors. In a standard t-test between the ICI3 and each of the ARM instruments, the p-value was 0.11 at the lowest (TSI) and typically 0.5 or greater, leading to failure to reject the null-hypothesis in all cases. This did not hold true in t-tests between different ARM instruments, and in many of these inter comparisons the null-hypothesis was rejected, suggesting a bias between cloud fraction data products from the different ARM

instruments. This may be explained by considering that the relationship between the cloud data products produced by these instruments can be described by a conceptual multi-dimensional space. Within this space the ICI3 cloud product lies between the cloud products produced by the ARM instruments.

Combining these comparisons with the uncertainty analysis showed there is a gap with potentially useful data between the threshold that produced the best correlation with ARM instruments and the ICI3 minimum cloud threshold derived for $\text{SNR} = 5$. This allows for an increased cloud sensitivity. These thin clouds sensed by the ICI3 were shown to compare well with an improved LIDAR cloud product that incorporated high thin clouds sensed by the micro-pulse LIDAR (MPL). These high-thin clouds tended to be measured during the Arctic winter by both the ICI and the MPL.

Alternative data processing techniques using decision trees and support vector machines were studied to improve data accuracy and reduce dependence on auxiliary instrument data, and the resulting accuracy is reported here. The work described in this project was part of the effort to develop a fourth-generation ICI ready to be deployed in the Arctic. This system will serve a critical role in developing our understanding of cloud cover in the Arctic, an important but poorly understood region of the world.

Improved Data Processing

The uncertainty analysis of the ICI3 demonstrated that the standard direct data processing based on the difference between the measured sky radiance and a modeled clear sky radiance has too much uncertainty to allow for consistent detection of thin

clouds. This led to the implementation of the gradient-and-time (v4) algorithm and the support vector machine cloud classifier.

Gradient-and-Time (v4) Algorithm The gradient-and-time or v4 algorithm is based on an understanding of how a clear sky should change, both in angle across the image (gradients) and between subsequent images (time). This allows regions of clear sky to be detected independently of the standard data processing. These clear sky regions are then used to update the residual radiance images over time. This improved processing had a theoretical cloud detection limit of an optical depth = 0.17, assuming all sources of slowly changing uncertainty are removed from the imagery, resulting in a radiance uncertainty of $0.19 \text{ W}/(\text{m}^2 \text{ sr})$. At ARM NSA, it was estimated that this algorithm produced an uncertainty of $0.25 \text{ W}/(\text{m}^2 \text{ sr})$, leading to a minimum detectable cloud with an optical depth of 0.28, double that of the noise-equivalent cloud in the ICI3 and half that of the direct data processing minimum cloud. This algorithm also demonstrated the ability to correct for known biases in the ICI3 data, leading to a consistent cloud product across data sets that incorporated different camera calibrations, and a consistent estimated uncertainty in these data sets. This demonstrated that the gradient-and-time method did reduce the uncertainty in the cloud detection systems.

The Cloud Classification Support Vector Machine The implementation of a SVM in the ICI3 data analysis started as a method to replace the cloud threshold system with one based on a radiometric difference using residual radiance and other parameters to improve cloud identification. During development, leave-one-out analyses on the SVM

input parameters showed that the radiometric image parameters and atmospheric parameters only resulted in a decreased testing accuracy 2 to 3% when dropped.

This led to the development of a multi-class SVM cloud detection system that allowed the ICI to operate independently of external instruments, and even independently of an absolute radiometric calibration. This cloud classifier has been demonstrated on the ICI3 that currently provides a cloud / no cloud detection consistent with the ARM instruments and the standard ICI3 data processing. This multi-class SVM also demonstrated the ability to separate the clouds into different cloud thicknesses. This method could be adapted to allow for a cloud optical depth characterization for an uncalibrated ICI system.

Time series comparisons between the SVM-derived cloud fraction and the ICI3 cloud fraction showed differences where, depending on the SVM implementation, the cloud fraction was either higher (SVM2) or lower (SVM1) than the ICI during the same period. This suggests that the SVM could be tuned to produce a result consistent with the ICI3. This approach may just build any biases present in the ICI3 into the SVM and further experiments comparing to other ARM instruments and improved cloud data products could improve the SVM accuracy without less bias.

The SVM is a major step forward in ICI data processing, as it removes the ICI dependence on external instruments for precipitable water vapor and surface temperature, and runs without any atmospheric model. Earlier ICI versions required the instrument to be deployed at locations where a history of radiosonde data was available to derive an atmospheric model. Removing this dependence could improve ICI data from

deployments at sites without a history of radiosondes, such as the current ICI deployment at the Goldstone Deep Space Communication Complex, or future deployments at remote Arctic locations. The current deployments of multiple ICI3 systems and data from previous deployments do provide the data necessary to study the performance and the generality of the SVM classifier, which could lead to a truly independent ICI system.

In Conclusion

The climate of the Arctic is changing faster than the global average, and the rate of this change is not reflected in our current climate models. To improve these models our understanding of the radiative impact of Arctic clouds needs to be improved. The ICI3 has the ability to improve this understanding by providing long-term data sets of day and night clouds that use a consistent and illumination-independent detection method. Of particular interest are thin clouds. This work has addressed the thin cloud sensitivity of the ICI3, shown to be less than ideal using the standard methods, and has provided an improved data processing method to increase thin cloud sensitivity.

To address the need for improved climatological data, the ICI could be deployed as part of the Arctic Observing Network. For these instruments to be widely deployed, their independence must be increased. ARM NSA provided a platform to study these instruments and study the SVM-based data processing routines that could lead to an independent ICI. Although these routines are still preliminary, they show great promise toward the development of a reliable, fully independent ICI cloud detection system. Development of such a system would allow for an ICI that could be widely deployed

with reduced pre-analysis for the location. This, in turn, will allow the ICI cloud imaging technique to become a general and widely implemented method of cloud detection on the cloudy planet Earth on which we all live.

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